

CAN KNOWLEDGE EDITING REALLY CORRECT HALLUCINATIONS?

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ABSTRACT

Large Language Models (LLMs) suffer from hallucinations, referring to the non-factual information in generated content, despite their superior capacities across tasks. Meanwhile, knowledge editing has been developed as a new popular paradigm to correct the erroneous factual knowledge encoded in LLMs with the advantage of avoiding retraining from scratch. However, one common issue of existing evaluation datasets for knowledge editing is that **they do not ensure LLMs actually generate hallucinated answers to the evaluation questions before editing**. When LLMs are evaluated on such datasets after being edited by different techniques, it is hard to directly adopt the performance to assess the effectiveness of different knowledge editing methods in correcting hallucinations. Thus, the fundamental question remains insufficiently validated: *Can knowledge editing really correct hallucinations in LLMs?* We proposed HalluEditBench to holistically benchmark knowledge editing methods in correcting real-world hallucinations. First, we rigorously construct a massive hallucination dataset with 9 domains, 26 topics and more than 6,000 hallucinations. Then, we assess the performance of knowledge editing methods in a holistic way on five dimensions including *Efficacy*, *Generalization*, *Portability*, *Locality*, and *Robustness*. Through HalluEditBench, we have provided new insights into the potentials and limitations of different knowledge editing methods in correcting hallucinations, which could inspire future improvements and facilitate the progress in the field of knowledge editing.

1 INTRODUCTION

Large Language Models (LLMs) have shown superior performance in various tasks (Zhao et al., 2023). However, one critical weakness is that they may output hallucinations, referring to the non-factual information in generated content, for reasons such as the limit of models’ internal knowledge scope or fast-changing world facts (Zhang et al., 2023). Considering the high cost of retraining LLMs from scratch, knowledge editing has been designed as a new paradigm to correct erroneous or outdated factual knowledge in LLMs (Wang et al., 2023b).

Although there are many existing question-answering datasets such as WikiData_{recent} (Cohen et al., 2024), ZsRE (Yao et al., 2023), and WikiBio (Hartvigsen et al., 2024) widely used for knowledge editing evaluation, one common issue is that they do not verify whether LLMs, before applying knowledge editing, actually generate hallucinated answers to the evaluation questions. When such datasets are adopted to evaluate the performance of LLMs after being edited, it is hard to directly use the scores to judge the effectiveness of different knowledge editing techniques in correcting hallucinations, which is the motivation of applying knowledge editing to LLMs. To better illustrate this point, following the evaluation setting in (Zhang et al., 2024b), we conducted a preliminary study to examine the pre-edit and post-edit performances of Llama2-7B on the aforementioned

Method	WikiData _{recent}	ZsRE	WikiBio
Pre-edit	47.40	37.49	61.35
Post-edit (ROME)	97.37	96.86	95.91
Post-edit (MEMIT)	97.10	95.86	94.68
Post-edit (FT-L)	56.30	53.82	66.70
Post-edit (FT-M)	100.00	99.98	100.00
Post-edit (LoRA)	100.00	100.00	100.00

Table 1: Performance measured by **Accuracy (%)** of Llama2-7B before editing (“Pre-edit”) and after applying typical knowledge editing methods (“Post-edit”) on common existing evaluation datasets.

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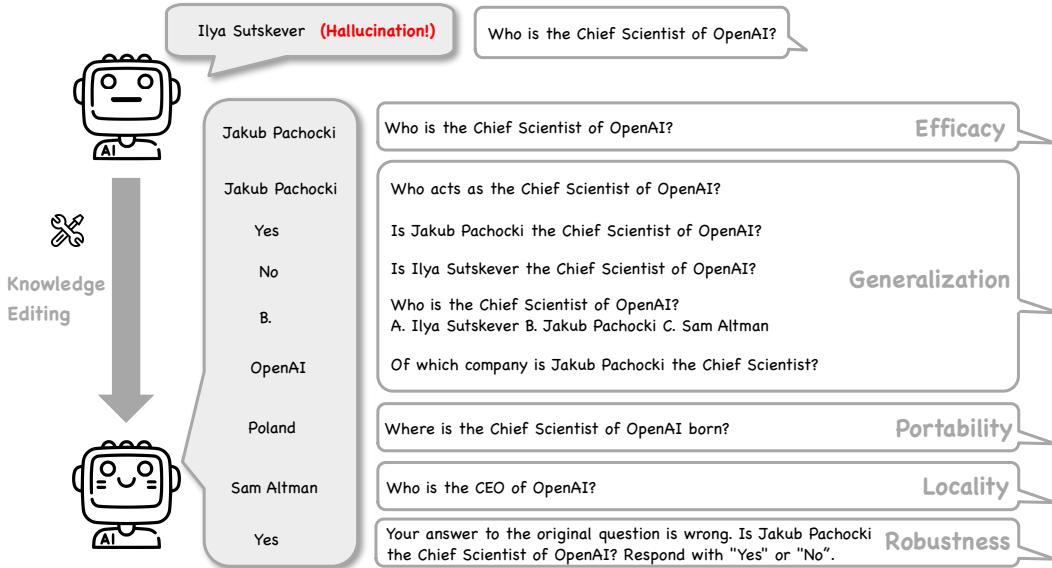


Figure 1: **Framework of HalluEditBench.** For real-world hallucinations, we holistically assess the performance of knowledge editing on *Efficacy*, *Generalization*, *Portability*, *Locality*, and *Robustness*.

three evaluation datasets. As shown in Table 1, we can clearly observe that Llama2-7B achieves a relatively high performance, measured by the rate of answering the evaluation questions correctly (**Accuracy (%)**), even before applying knowledge editing techniques. Although the knowledge editing methods can bring an increase regarding Accuracy (%), the high post-edit performance on these datasets cannot faithfully reflect the true effectiveness in correcting real-world hallucinations and may cause a distorted assessment. Thus, the fundamental question remains insufficiently validated: ***Can knowledge editing really correct hallucinations in LLMs?***

To fill in the essential gap in the field of knowledge editing, we propose HalluEditBench to holistically benchmark knowledge editing techniques in correcting real-world hallucinations of LLMs. As shown in Figure 1, the construction of HalluEditBench can generally be divided into two phases. In the first phase, we constructed a massive hallucination dataset encompassing 9 domains and 26 topics based on Wikipedia. For each of Llama2-7B, Llama3-8B, and Mistral-v0.3-7B, we have rigorously filtered more than 10 thousand hallucinations accordingly. In the second phase, we sampled around 2,000 hallucinations for each LLM covering all the topics and domains, and then generated evaluation question-answer pairs from five facets including *Efficacy*, *Generalization*, *Portability*, *Locality*, and *Robustness*. Through extensive empirical investigation on performance of 7 typical knowledge editing techniques, including FT-L (Meng et al., 2022), FT-M (Zhang et al., 2024b), MEMIT (Meng et al., 2023), ROME (Meng et al., 2022), LoRA (Hu et al., 2022), ICE (Zheng et al., 2023), and GRACE (Hartvigsen et al., 2024), regarding the aforementioned five dimensions, we have provided novel insights into their potentials and limitations. A summary of the insights is as follows:

- **The effectiveness of knowledge editing methods in correcting real-world hallucinations could be far from what their performance on existing datasets suggests**, reflecting the potential unreliability of current assessment of different knowledge editing techniques. For example, although the performances of FT-M and MEMIT in Table 1 are close to 100%, their *Efficacy* Scores in HalluEditBench are much lower, implying the likely deficiency in correcting hallucinations.
- **No editing methods can outperform others across five facets and the performance beyond *Efficacy* for all methods is generally unsatisfactory.** Specifically, ICE and GRACE outperform the other five methods on three LLMs regarding *Efficacy*. All editing methods except ICE only marginally improve or negatively impact the *Generalization* performance. Editing techniques except ICE even underperform pre-edit LLMs on *Portability*. FT-M and ICE surpass others on *Locality* performance. ICE has a poor *Robustness* performance compared to other methods.
- **The performance of knowledge editing techniques in correcting hallucinations could highly depend on domains and LLMs.** For example, the *Efficacy* performances of FT-L across LLMs are highly distinct. Domains have a large impact on the *Locality* performance of ICE.

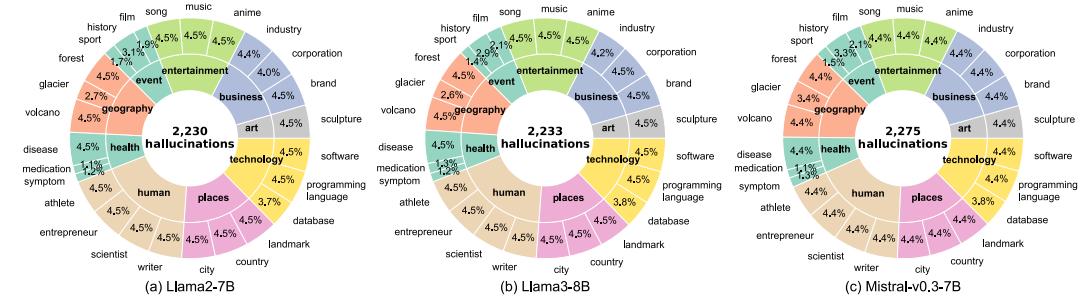


Figure 2: Statistics of HalluEditBench Across Topics and Domains.

2 HalluEditBench: HOLISTICALLY BENCHMARKING KNOWLEDGE EDITING METHODS IN CORRECTING REAL-WORLD HALLUCINATIONS

In this section, we will introduce the details of HalluEditBench, including the construction of the massive LLM hallucination dataset, the generation of evaluation question-answering pairs from five dimensions, evaluation metrics and the benchmarked knowledge editing techniques.

2.1 HALLUCINATION DATASET CONSTRUCTION

The goal of knowledge editing can generally be defined as transforming existing factual knowledge in the form of a knowledge triplet (subject s , relation r , object o) into a new one (subject s , relation r , object o^*). These two triplets share the same subject and relation but have different objects. A knowledge editing operation can be represented as $e = (s, r, o, o^*)$. Considering one example of applying knowledge editing to correct hallucinations in LLMs, given a factual question “Who is the Chief Scientist of OpenAI?”, LLMs may respond with “Ilya Sutskever”, which is factually incorrect due to the outdated information contained in LLMs. The editing operation can be $e = (s = \text{OpenAI}, r = \text{Chief Scientist}, o = \text{Ilya Sutskever}, o^* = \text{Jakub Pachocki})$. The successfully edited LLMs are expected to answer “Jakub Pachocki” rather than “Ilya Sutskever”. Thus, we need to collect a large scale of knowledge triplets and factual questions to filter hallucinations.

Following existing editing datasets (*e.g.*, WikiData_{recent} (Cohen et al., 2024) and WikiBio (Hartvigsen et al., 2024)), we also choose Wikipedia as the factual knowledge source. In the *first* step, we retrieved 143,557 raw knowledge triplets using Wikidata Query Service (WDQS) from 26 topics, which can be categorized into 9 domains including *art*, *business*, *entertainment*, *event*, *geography*, *health*, *human*, *places*, and *technology*. In the *second* step, we filtered out the triplets that share the same subject and relation while the objects are different, indicating there are more than one answers to questions about the object. When we construct factual questions and compare LLM-generated answers with the triplets, it would be hard to determine whether LLMs actually hallucinate the questions. For example, for two triplets (Canada, diplomatic relation, India) and (Canada, diplomatic relation, Greece), there are multiple answers to the question “What country has diplomatic relation with Canada?” In the *third* step, following (Wang et al., 2024e), we applied rules to convert knowledge triplets into factual questions with objects as the ground-truth answers. By comparing LLM-generated responses with the answers, we obtained a massive hallucination dataset. Specifically, we collected 12,619, 13,210, and 14,366 hallucinations for Llama2-7B, Llama3-8B, and Mistral-v0.3-7B respectively. Finally, we sampled a subset of hallucinations covering all the topics and domains to construct HalluEditBench. The distribution statistics are shown in Figure 2.

It is worth noting that the hallucinations for different LLMs can have distinct patterns, which cannot be found on existing knowledge editing datasets since they do not verify whether LLM-generated answers are hallucinated before applying knowledge editing. **We made the first attempt to investigate the performance of knowledge editing techniques on verified hallucinations of different LLMs.**

2.2 EVALUATION QA PAIR GENERATION AND METRICS

After constructing the hallucination dataset, we proposed to holistically assess the performance of knowledge editing methods in correcting hallucinations from five facets including *Efficacy*, *Generalization*, *Portability*, *Locality*, and *Robustness*. First, we leveraged GPT-4o to generate evaluation

question-answering pairs for each facet based on the hallucination dataset as well as the factuality verification questions in Section 2.1. Then we also manually inspect their quality. One example of the evaluation QA pairs for each facet is shown in Figure 1 (More examples are in Appendix E). The specific prompt design for GPT-4o is shown in Appendix A.

Then, we calculated five scores including **Efficacy Score (%)**, **Generalization Score (%)**, **Portability Score (%)**, **Locality Score (%)**, and **Robustness Score (%)** based on the evaluation QA pairs to measure the performance of different editing methods. Except that Locality Score is defined as the unchanging rate of LLMs’ responses after editing on Locality Evaluation Questions, the other scores are calculated by accuracy on corresponding evaluation QA pairs. More details are as follows:

Facet 1: Efficacy Efficacy Evaluation Questions are the same as the factuality verification questions in the hallucination collection to ensure the pre-edit performance is 0 regarding Efficacy Score. Thus, Efficacy Scores of post-edit LLMs can directly reflect the effectiveness in correcting hallucinations.

Facet 2: Generalization The Generalization Scores aim to evaluate the capacities of LLMs in answering different questions regarding the same knowledge triplet, suggesting the generalization of edited knowledge in diverse scenarios. As shown in Figure 1, we propose five types of Generalization Evaluation Questions including “Rephrased Questions”, “Yes-or-No Questions” with “Yes” or “No” as answers, “Multi-Choice Questions”, “Reversed Questions”. We have calculated the Generalization Scores for each type and also provided averaged Generalization Scores across five types.

Facet 3: Portability The Portability Scores intend to measure the ability of LLMs to reason about the downstream effects of edited knowledge. Thus, we design the Efficacy Evaluation Questions with N hops ($N = 1 \sim 6$) as Portability Evaluation Questions. When $N = 2$, the example is shown in Figure 1. When the answer to the question “Who is the Chief Scientist of OpenAI?” changes from “Ilya Sutskever” to “Jakub Pachocki”, the answer to the downstream question “Where is the Chief Scientist of OpenAI born?” should also change from “Russia” to “Poland”.

Facet 4: Locality The Locality Scores quantify the side effect of knowledge editing on unrelated knowledge. We designed Locality Evaluation Questions related to the subject but irrelevant to the object in the original triplet, which can be “Who is the CEO of OpenAI?” for the aforementioned example. Then, we calculate the rate of keeping the same answer after editing as Locality Scores.

Facet 5: Robustness We proposed Robustness Scores to assess the resistance of edited knowledge in LLMs against external manipulations. Although literature has studied the general sycophancy behavior of LLMs (Sharma et al., 2024b), the robustness of edited factual knowledge against users’ distractions (e.g., “Your answer to the original question is wrong.”) is under-explored. After post-edit LLMs are tested with Efficacy Evaluation Questions, we further prompted them with Robustness Evaluation Questions, which are exemplified in Figure 1, for M turns ($M = 1 \sim 10$) and calculated the rate of “Yes” for each round as the Robustness Scores, reflecting the extent to which LLMs insist on the corrected knowledge. Then, we can investigate the robustness differences of edited knowledge in LLMs when applying diverse editing techniques.

2.3 KNOWLEDGE EDITING TECHNIQUES

We propose to categorize the majority of existing knowledge editing techniques into the following 4 types and chose 7 representative techniques (more details are in Appendix B) in HalluEditBench.

- **Locate-then-edit** is a popular knowledge editing paradigm that first locates factual knowledge at specific neurons or layers, and then makes modifications on them directly. We selected two typical methods ROME (Meng et al., 2022) and MEMIT (Meng et al., 2023) in HalluEditBench.
- **Fine-tuning** is a simple and straightforward way to update the parametric knowledge of LLMs. We selected three variations FT-L (Meng et al., 2022), FT-M (Zhang et al., 2024b), and LoRA (Hu et al., 2022), which mitigate the catastrophic forgetting and overfitting issues of standard fine-tuning.
- **In-Context Editing** is a training-free paradigm that associates LLMs with in-context knowledge directly (Zheng et al., 2023; Shi et al., 2024; Fei et al., 2024). We adopted a simple baseline ICE method in (Zheng et al., 2023) that puts the new fact in the context and requires no demonstrations.
- **Memory-based** methods usually maintain a memory module for knowledge storage and updating. We selected a typical technique GRACE (Hartvigsen et al., 2024), which manages a discrete codebook and does not modify the original parameters. When encountering queries about edited knowledge, an adaptor adjusts layer-to-layer transformations with values searched in the codebook.

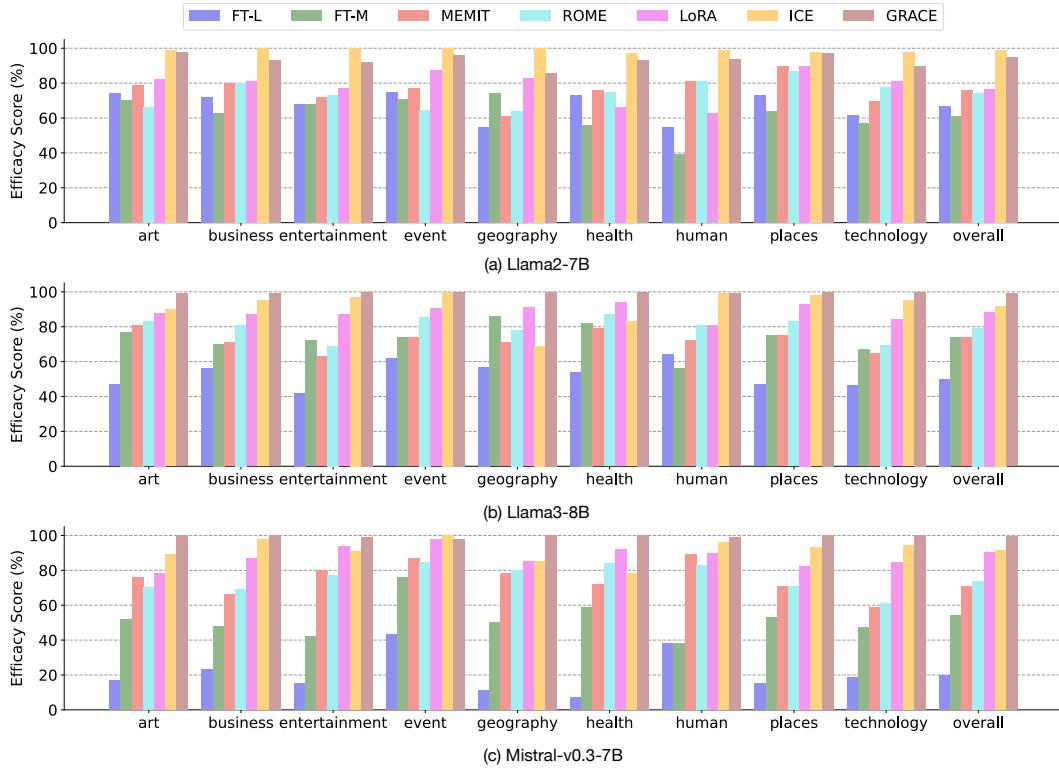


Figure 3: **Efficacy Scores of Knowledge Editing Methods.** The “overall” refers to the Efficacy Score (%) on the whole HalluEditBench embracing 9 domains for different methods. The Efficacy Score on each domain is also reported. Efficacy scores (%) are measured by the accuracy on Efficacy Evaluation Question-answer Pairs, where the pre-edit scores of each LLM are ensured 0.

3 RESULTS AND ANALYSIS

In this section, we comprehensively analyze the experiment results on 9 domains and the overall performance on the whole HalluEditBench for different knowledge editing techniques from five facets including *Efficacy*, *Generalization*, *Portability*, *Locality*, and *Robustness*.

3.1 FACET 1: EFFICACY

Figure 3 shows the Efficacy Score performance of post-edit LLMs in each domain and the whole HalluEditBench. Since we have ensured the LLMs’ pre-edit Efficacy Score is 0, Figure 3 can directly reflect the effectiveness of different knowledge editing techniques in correcting real-world hallucinations. Thus, we find that **the effectiveness of some techniques can be far from what their performance on previous datasets suggests**, implying the potential unreliability of performance on previous datasets. For example, as shown in Table 1, although FT-M achieves near 100% performance in existing datasets such as WikiDatarecent, ZsRE, and WikiBio, its overall Efficacy Scores on Llama2-7B and Mistral-v0.3-7B are only around 60%. There is a similar performance drop for MEMIT.

Second, based on the overall Efficacy Scores across three LLMs, **the following effectiveness ranking generally holds: $\text{FT-L} < \text{FT-M} < \text{MEMIT} < \text{ROME} < \text{LoRA} < \text{ICE} < \text{GRACE}$** . We can observe that ICE and GRACE, which both preserve original weights in LLMs, outperform the other methods, implying **the potential disadvantage of directly modifying parameters for editing knowledge**.

Third, we notice that **efficacy scores of knowledge editing techniques could highly depend on domains and LLMs**. For example, the scores of FT-L on different domains and LLMs could be highly distinct. Performance of FT-L and FT-M on Llama3-8B is higher than that on Mistral-v0.3-7B.

Insight 1: (1) The current assessment of knowledge editing could be unreliable; (2) ICE and GRACE outperform parameter-modifying editing techniques such as fine-tuning and “Locate-then-Edit” methods on *Efficacy*; (3) Domains and LLMs could have a high impact on *Efficacy*.

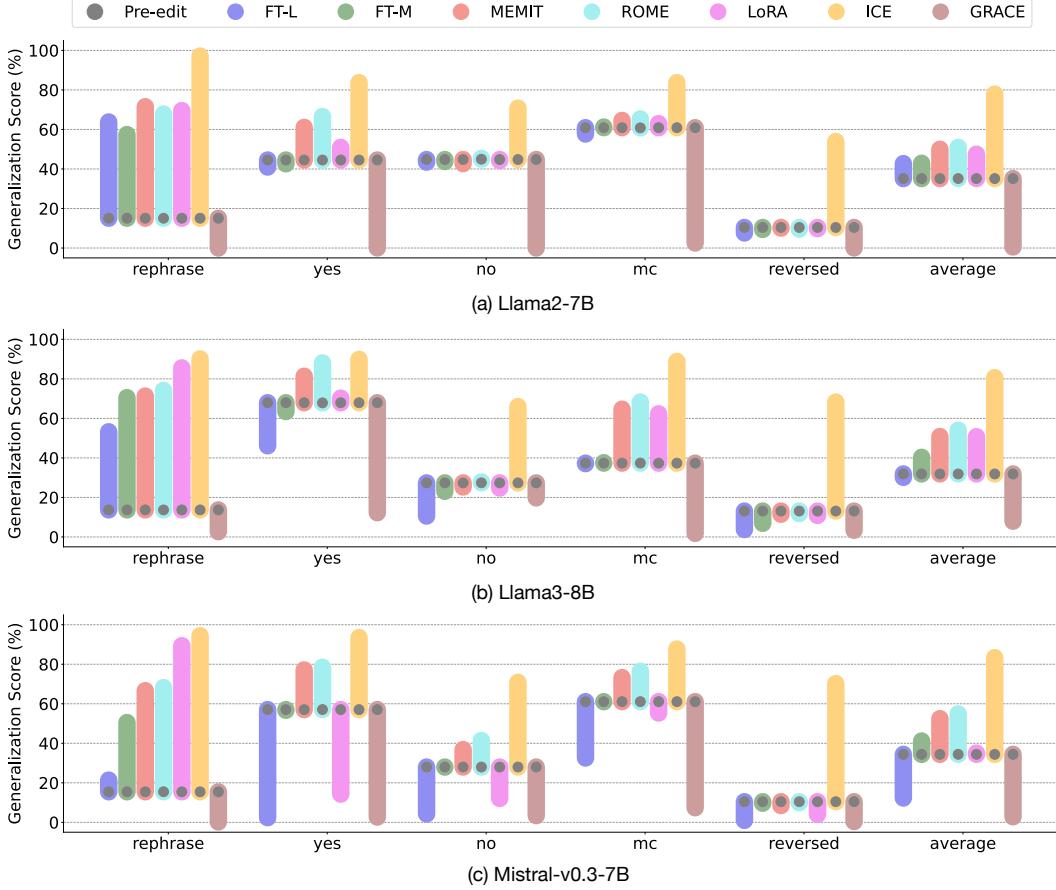


Figure 4: **Generalization Scores of Knowledge Editing Methods.** Generalization Scores (%) are measured by accuracy on five types of Generalization Evaluation Questions including Rephrased Questions (“rephrase”), Yes-or-No Questions with Yes or No as answers (“yes” or “no”), Multi-Choice Questions (“mc”), Reversed Questions (“reversed”). The “average” refers to averaged scores over five question types. The figure only shows the overall Generalization Scores for each type on the whole HalluEditBench. Generalization Scores for each domain are given in Appendix D.1.

3.2 FACET 2: GENERALIZATION

Figure 4 shows both the pre-edit and post-edit Generalization Scores for different knowledge editing techniques on three LLMs. It is worth noting that the pre-edit performance is the same for different techniques and not zero, illustrating that **the manifestation of hallucination actually depends on the design of question prompts**. Given a group of diverse question prompts for the same knowledge triplet, LLMs may hallucinate some questions but answer others correctly.

Surprisingly, we find that **post-edit Generalization Scores could even be lower than pre-edit scores** for the same LLM and question type, demonstrating the potential negative effect caused by knowledge editing. In more detail, we can observe a clear performance drop for GRACE across all the question types, and for FT-L and LoRA on some question types.

Comparing the ranking of Efficacy Scores in Figure 3 with Figure 4, we can explicitly see that **higher Efficacy Scores do not also necessarily indicate higher Generalization Scores**. Especially, although GRACE almost surpasses all the other editing techniques regarding Efficacy Scores, it largely degrades the Generalization Scores compared to pre-edit performance. In addition, **all editing methods except ICE only marginally improve or even hurt Generalization Scores**.

Insight 2: (1) The manifestation of hallucination depends on question design; (2) Higher *Efficacy Scores* do not also necessarily indicate higher *Generalization Scores*; (3) All editing techniques except ICE only marginally improve or negatively impact the *Generalization* performance.

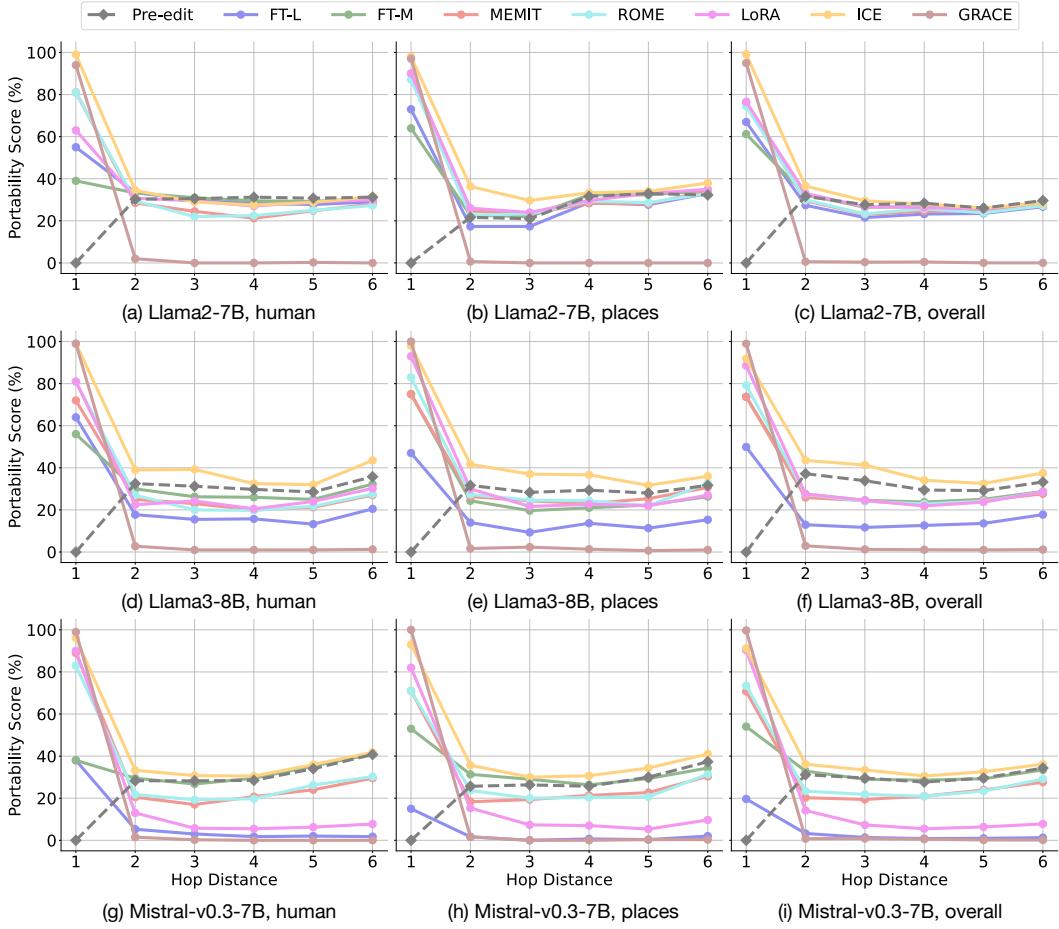


Figure 5: Portability Scores of Knowledge Editing Methods. Portability Scores (%) are measured by the accuracy on Portability Evaluation Questions, which are Efficacy Evaluation Questions with N hops ($N = 1 \sim 6$). The Portability Evaluation Questions are the same as Efficacy Evaluation Questions when N is 1. The Portability Scores on two domains “human” and “places” are reported in the figure. The results for more domains are given in Appendix D.2. The “overall” refers to the Portability Score (%) on the whole HalluEditBench embracing 9 domains.

3.3 FACET 3: PORTABILITY

Figure 5 demonstrates the pre-edit and post-edit Portability Scores for Portability Evaluation Questions with N hops ($N = 1 \sim 6$). When $N = 1$, the Portability Evaluation Questions are the same as Efficacy Evaluation Questions, suggesting that the Portability Scores are 0. Similar to Figure 4, we discover that the pre-edit Portability Scores are not zero for $2 \sim 6$ hops, indicating **LLMs do not necessarily need to reason based on single-hop knowledge to answer multi-hop questions**. We hypothesize that this is because LLMs may directly memorize the answers to multi-hop questions.

We surprisingly find that except that ICE may bring marginal improvement to the pre-edit performance, **the other knowledge editing techniques even mostly underperform pre-edit Portability Scores**, showing another type of negative effect of knowledge editing and **LLMs cannot really reason with the edited knowledge in multi-hop questions** regardless of knowledge editing methods. Comparing single-hop and multi-hop performance, we observe a sharp decrease for all the editing methods, which further underscores the challenges of answering multi-hop questions with edited knowledge.

Insight 3: (1) LLMs may memorize answers rather than reason based on single-hop knowledge for multi-hop questions; (2) Editing methods except ICE mostly underperform pre-edit Portability Scores, implying LLMs cannot really reason with edited knowledge in multi-hop questions.

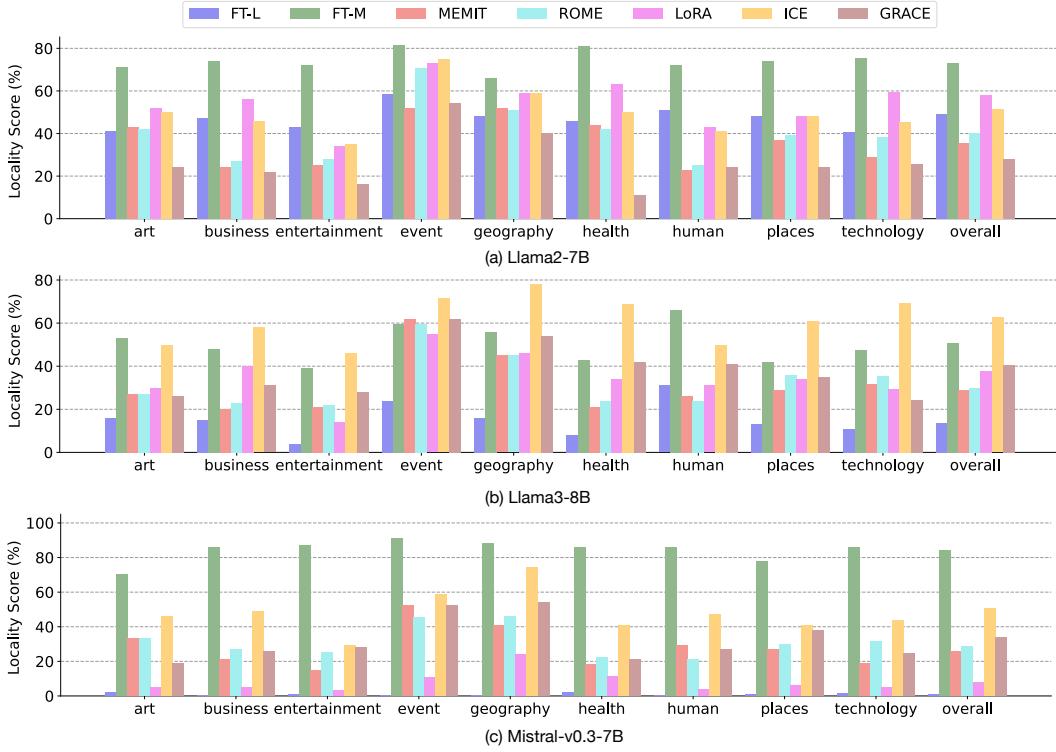


Figure 6: Locality Scores of Knowledge Editing Methods. Locality Scores (%) are measured by the unchanging rate on Locality Evaluation Questions after applying knowledge editing methods on LLMs. A higher Locality Score indicates that there is a higher percentage of LLMs’ answers to the unrelated questions keeping the same and a less side effect on general knowledge in LLMs. The “overall” refers to the Locality Score (%) on the whole HalluEditBench embracing 9 domains for different methods. The Locality Score on each domain is also reported in the figure.

3.4 FACET 4: LOCALITY

Figure 6 shows the Locality Scores of different editing techniques in each domain and the whole HalluEditBench, reflecting the side effect of knowledge editing on unrelated knowledge encoded in LLMs. Based on the overall Locality Scores, we can observe that **the performance of all editing methods except FT-M and ICE is unsatisfactory**. In particular, the overall Locality Scores for all editing techniques except FT-M and ICE on Llama3-8B and Mistral-v0.3-7B are below 40%, suggesting a high undesired impact on LLMs’ answers to unrelated factual questions, though FT-M achieves an overall score of around 80% on Mistral-v0.3-7B and ICE gains 60% on Llama3-8B.

Furthermore, we notice that **domains and LLMs have a high impact on the Locality Scores of knowledge editing methods**. For example, the Locality Score for ICE in the geography domain in Llama3-8B is around 80%, while the performance drops to only about 40% in the entertainment domain for the same LLM. Although FT-M obtains a Locality Score of around 80% in the entertainment domain on Mistral-v0.3-7B, its performance in the same domain on Llama3-8B is below 40%.

Due to the impact of LLMs, we observe that **the rankings by Locality Scores for editing techniques on different LLMs are highly distinct**. For example, the Locality ranking on Llama2-7B is GRACE < MEMIT < ROME < FT-L < ICE < LoRA < FT-M. However, the ranking changes to FT-L < LoRA < MEMIT < ROME < GRACE < ICE < FT-M on Mistral-v0.3-7B. Comparing Figure 3 with Figure 6, we find **there is no noticeable correlation between Efficacy and Locality for different editing techniques**. FT-M achieves relatively high Locality Scores despite its low Efficacy Scores.

Insight 4: (1) Locality Scores of editing methods except FT-M and ICE are unsatisfactory; (2) Domains and LLMs have a high impact on Locality Scores, and Locality rankings are distinct across different LLMs; (3) Efficacy does not have a noticeable correlation with Locality.

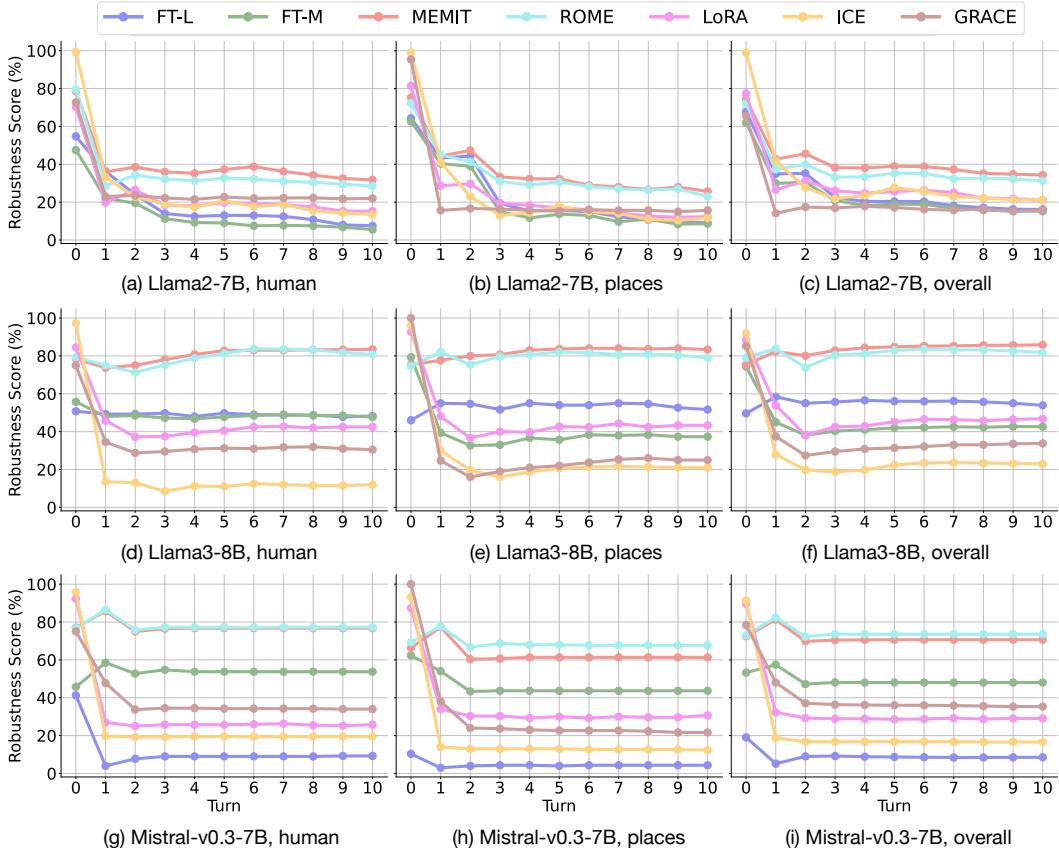


Figure 7: Robustness Scores of Knowledge Editing Methods. Robustness Scores are calculated by the accuracy on Robustness Evaluation Questions with M turns ($M = 1 \sim 10$). We regard Efficacy Scores as the Robustness Scores when M is 0. The Robustness Scores on two domains ‘‘human’’ and ‘‘places’’ are reported in the figure. The results for more domains are given in Appendix D.3. The ‘‘overall’’ refers to the Robustness Score (%) on the whole HalluEditBench embracing 9 domains.

3.5 FACET 5: ROBUSTNESS

We proposed Robustness Scores (%) to evaluate the resistance of edited knowledge against distractions in prompts. Initially ($M = 0$), LLMs are assessed with Efficacy Evaluation Questions. Then ($M = 1 \sim 10$), LLMs are sequentially prompted with Robutness Evaluation Questions, which are exemplified in Figure 1, for M turns. Robustness Scores are calculated with the percentage of ‘‘Yes’’ in each round. A higher Robustness Score indicates that there is a larger percentage of LLMs can resist external manipulations in the prompt and a higher extent of robustness for the edited knowledge.

First, based on overall Robustness Scores, we observe that **LLMs themselves have a large impact on the robustness of edited knowledge. The same editing technique could show distinct trends as turns increase on different LLMs.** For example, all editing methods have a sharp drop when turns go up on Llama2-7B, showing a low level of robustness. However, MEMIT, ROME, FT-M on Llama3-8B and MEMIT, ROME, FT-M, FT-L on Mistral-v0.3-7B maintain almost the same performance as turns increase, suggesting a relatively high level of robustness for the edited knowledge.

Then, we notice that **both ICE and GRACE have a low level of robustness** though they outperform the other five editing techniques regarding Efficacy Scores, showing **the potential weaknesses on robustness of parameter-preserving knowledge editing methods.** However, parameter-modifying editing techniques do not necessarily have high robustness, which is exemplified by LoRA.

Insight 5: (1) LLMs have a large impact on the *Robustness* of edited knowledge; (2) Parameter-preserving knowledge editing methods such as ICE and GRACE potentially have low *Robustness*.

4 RELATED WORK

Knowledge editing techniques have attracted increasing attention for their efficiency advantages in addressing obsolete or hallucinated information in LLMs (Wang et al., 2023b; Zhang et al., 2024b). In general, the existing editing techniques can be categorized into four types including *Locate-then-edit* (Meng et al., 2022; 2023), *Fine-tuning based* (Gangadhar & Stratos, 2024; Zhu et al., 2020; Wang et al., 2024a), *In-Context Editing* (Zheng et al., 2023; Shi et al., 2024; Fei et al., 2024), and *Memory-based* (Wang et al., 2024d; Hartvigsen et al., 2024; Mitchell et al., 2022; Yu et al., 2023). Recently, many benchmarks have been built to investigate the properties of knowledge editing from different perspectives (Rosati et al., 2024; Wu et al., 2023; Ge et al., 2024a; Ma et al., 2023; Wei et al., 2023; 2024a; Zhong et al., 2023; Lin et al., 2024; Huang et al., 2024; Liu et al., 2024b; Akyürek et al., 2023; Li et al., 2024a;d; 2023b; Gu et al., 2024; Powell et al., 2024). For example, Gu et al. (2024) proposed a benchmark to assess the side effect of 4 popular editing methods on 3 LLMs across 8 general capacity tasks. Rosati et al. (2024) built a new evaluation protocol to measure the efficacy and impact of knowledge editing in long-form generation. Wei et al. (2024a) introduced a multilingual knowledge editing benchmark embracing five languages. However, considering the fundamental motivation of applying knowledge editing to LLMs, which is to correct hallucinations, there is a pressing need to build a real-world hallucination dataset with rigorous verification and systematically analyze the performance of different editing methods. Thus, we proposed HalluEditBench to fill in the gap and provided new insights to facilitate the progress in the field of knowledge editing.

5 CONCLUSION

In this paper, we have built a new benchmark HalluEditBench to holistically assess diverse knowledge editing techniques in correcting real-world hallucinations. First, we carefully construct a massive hallucination dataset based on Wikipedia with 9 domains, 26 topics, and more than 6,000 hallucinations. Then, we systematically investigate the performance of different knowledge editing methods from five perspectives including *Efficacy*, *Generalization*, *Portability*, *Locality*, and *Robustness*. With extensive empirical experiment results, we have offered valuable insights for the potentials and limitations of typical knowledge editing methods, which could inspire more future improvements.

REFERENCES

- Afra Feyza Akyürek, Eric Pan, Garry Kuwanto, and Derry Wijaya. Dune: Dataset for unified editing. *ArXiv preprint*, abs/2311.16087, 2023. URL <https://arxiv.org/abs/2311.16087>.
- Baolong Bi, Shenghua Liu, Lingrui Mei, Yiwei Wang, Pengliang Ji, and Xueqi Cheng. Decoding by contrasting knowledge: Enhancing llms' confidence on edited facts. *ArXiv preprint*, abs/2405.11613, 2024a. URL <https://arxiv.org/abs/2405.11613>.
- Baolong Bi, Shenghua Liu, Yiwei Wang, Lingrui Mei, Hongcheng Gao, Junfeng Fang, and Xueqi Cheng. Struedit: Structured outputs enable the fast and accurate knowledge editing for large language models. *ArXiv preprint*, abs/2409.10132, 2024b. URL <https://arxiv.org/abs/2409.10132>.
- Baolong Bi, Shenghua Liu, Yiwei Wang, Lingrui Mei, Hongcheng Gao, Yilong Xu, and Xueqi Cheng. Adaptive token biaser: Knowledge editing via biasing key entities. *arXiv preprint arXiv:2406.12468*, 2024c.
- Yuchen Cai, Ding Cao, Rongxi Guo, Yaqin Wen, Guiquan Liu, and Enhong Chen. Editing knowledge representation of language lodel via rephrased prefix prompts. *ArXiv preprint*, abs/2403.14381, 2024a. URL <https://arxiv.org/abs/2403.14381>.
- Yuchen Cai, Ding Cao, Rongxi Guo, Yaqin Wen, Guiquan Liu, and Enhong Chen. Locating and mitigating gender bias in large language models. *ArXiv preprint*, abs/2403.14409, 2024b. URL <https://arxiv.org/abs/2403.14409>.
- Canyu Chen and Kai Shu. Combating misinformation in the age of llms: Opportunities and challenges. *AI Magazine*, 2024. doi: 10.1002/aaai.12188. URL <https://doi.org/10.1002/aaai.12188>.
- Canyu Chen, Baixiang Huang, Zekun Li, Zhaorun Chen, Shiyang Lai, Xiongxiao Xu, Jia-Chen Gu, Jindong Gu, Huaxiu Yao, Chaowei Xiao, Xifeng Yan, William Yang Wang, Philip Torr, Dawn Song, and Kai Shu. Can editing llms inject harm? *ArXiv preprint*, abs/2407.20224, 2024a. URL <https://arxiv.org/abs/2407.20224>.
- Qizhou Chen, Taolin Zhang, Dongyang Li, Longtao Huang, Hui Xue, Chengyu Wang, and Xiaofeng He. Lifelong knowledge editing for llms with retrieval-augmented continuous prompt learning. *ArXiv preprint*, abs/2405.03279, 2024b. URL <https://arxiv.org/abs/2405.03279>.
- Yuheng Chen, Pengfei Cao, Yubo Chen, Kang Liu, and Jun Zhao. Journey to the center of the knowledge neurons: Discoveries of language-independent knowledge neurons and degenerate knowledge neurons. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 38, pp. 17817–17825, 2024c.
- Yuheng Chen, Pengfei Cao, Yubo Chen, Kang Liu, and Jun Zhao. Knowledge localization: Mission not accomplished? enter query localization! *ArXiv preprint*, abs/2405.14117, 2024d. URL <https://arxiv.org/abs/2405.14117>.
- Keyuan Cheng, Muhammad Asif Ali, Shu Yang, Gang Ling, Yuxuan Zhai, Haoyang Fei, Ke Xu, Lu Yu, Lijie Hu, and Di Wang. Leveraging logical rules in knowledge editing: A cherry on the top. *ArXiv preprint*, abs/2405.15452, 2024a. URL <https://arxiv.org/abs/2405.15452>.
- Keyuan Cheng, Gang Lin, Haoyang Fei, Lu Yu, Muhammad Asif Ali, Lijie Hu, Di Wang, et al. Multi-hop question answering under temporal knowledge editing. *ArXiv preprint*, abs/2404.00492, 2024b. URL <https://arxiv.org/abs/2404.00492>.
- Roi Cohen, Eden Biran, Ori Yoran, Amir Globerson, and Mor Geva. Evaluating the ripple effects of knowledge editing in language models. *Transactions of the Association for Computational Linguistics*, 12:283–298, 2024.
- Jingcheng Deng, Zihao Wei, Liang Pang, Hanxing Ding, Huawei Shen, and Xueqi Cheng. Unke: Unstructured knowledge editing in large language models. *ArXiv preprint*, abs/2405.15349, 2024. URL <https://arxiv.org/abs/2405.15349>.

- Junfeng Fang, Houcheng Jiang, Kun Wang, Yunshan Ma, Xiang Wang, Xiangnan He, and Tat-seng Chua. Alphaedit: Null-space constrained knowledge editing for language models. *ArXiv preprint*, abs/2410.02355, 2024. URL <https://arxiv.org/abs/2410.02355>.
- Weizhi Fei, Xueyan Niu, Guoqing Xie, Yanhua Zhang, Bo Bai, Lei Deng, and Wei Han. Retrieval meets reasoning: Dynamic in-context editing for long-text understanding. *ArXiv preprint*, abs/2406.12331, 2024. URL <https://arxiv.org/abs/2406.12331>.
- Javier Ferrando, Gabriele Sarti, Arianna Bisazza, and Marta R Costa-jussà. A primer on the inner workings of transformer-based language models. *ArXiv preprint*, abs/2405.00208, 2024. URL <https://arxiv.org/abs/2405.00208>.
- Govind Gangadhar and Karl Stratos. Model editing by pure fine-tuning. *ArXiv preprint*, abs/2402.11078, 2024. URL <https://arxiv.org/abs/2402.11078>.
- Huaizhi Ge, Frank Rudzicz, and Zining Zhu. How well can knowledge edit methods edit perplexing knowledge? *ArXiv preprint*, abs/2406.17253, 2024a. URL <https://arxiv.org/abs/2406.17253>.
- Xiou Ge, Ali Mousavi, Edouard Grave, Armand Joulin, Kun Qian, Benjamin Han, Mostafa Arefiyan, and Yunyao Li. Time sensitive knowledge editing through efficient finetuning. *ArXiv preprint*, abs/2406.04496, 2024b. URL <https://arxiv.org/abs/2406.04496>.
- Hengrui Gu, Kaixiong Zhou, Xiaotian Han, Ninghao Liu, Ruobing Wang, and Xin Wang. Pokemqa: Programmable knowledge editing for multi-hop question answering. *ArXiv preprint*, abs/2312.15194, 2023. URL <https://arxiv.org/abs/2312.15194>.
- Jia-Chen Gu, Hao-Xiang Xu, Jun-Yu Ma, Pan Lu, Zhen-Hua Ling, Kai-Wei Chang, and Nanyun Peng. Model editing harms general abilities of large language models: Regularization to the rescue. *ArXiv preprint*, abs/2401.04700, 2024. URL <https://arxiv.org/abs/2401.04700>.
- Akshat Gupta, Anurag Rao, and Gopala Anumanchipalli. Model editing at scale leads to gradual and catastrophic forgetting. *ArXiv preprint*, abs/2401.07453, 2024. URL <https://arxiv.org/abs/2401.07453>.
- Tom Hartvigsen, Swami Sankaranarayanan, Hamid Palangi, Yoon Kim, and Marzyeh Ghassemi. Aging with grace: Lifelong model editing with discrete key-value adaptors. *Advances in Neural Information Processing Systems*, 36, 2024.
- Peter Hase, Mohit Bansal, Been Kim, and Asma Ghandeharioun. Does localization inform editing? surprising differences in causality-based localization vs. knowledge editing in language models. *Advances in Neural Information Processing Systems*, 36, 2024a.
- Peter Hase, Thomas Hofweber, Xiang Zhou, Elias Stengel-Eskin, and Mohit Bansal. Fundamental problems with model editing: How should rational belief revision work in llms? *ArXiv preprint*, abs/2406.19354, 2024b. URL <https://arxiv.org/abs/2406.19354>.
- Jason Hoelscher-Obermaier, Julia Persson, Esben Kran, Ioannis Konstas, and Fazl Barez. Detecting edit failures in large language models: An improved specificity benchmark. *ArXiv preprint*, abs/2305.17553, 2023. URL <https://arxiv.org/abs/2305.17553>.
- Cheng-Hsun Hsueh, Paul Kuo-Ming Huang, Tzu-Han Lin, Che-Wei Liao, Hung-Chieh Fang, Chao-Wei Huang, and Yun-Nung Chen. Editing the mind of giants: An in-depth exploration of pitfalls of knowledge editing in large language models. *ArXiv preprint*, abs/2406.01436, 2024. URL <https://arxiv.org/abs/2406.01436>.
- Edward J. Hu, Yelong Shen, Phillip Wallis, Zeyuan Allen-Zhu, Yuanzhi Li, Shean Wang, Lu Wang, and Weizhu Chen. Lora: Low-rank adaptation of large language models. In *The Tenth International Conference on Learning Representations, ICLR 2022, Virtual Event, April 25-29, 2022*. OpenReview.net, 2022. URL <https://openreview.net/forum?id=nZeVKeFYf9>.
- Wenyue Hua, Jiang Guo, Mingwen Dong, Henghui Zhu, Patrick Ng, and Zhiguo Wang. Propagation and pitfalls: Reasoning-based assessment of knowledge editing through counterfactual tasks. *ArXiv preprint*, abs/2401.17585, 2024. URL <https://arxiv.org/abs/2401.17585>.

Han Huang, Haitian Zhong, Tao Yu, Qiang Liu, Shu Wu, Liang Wang, and Tieniu Tan. Vlkeb: A large vision-language model knowledge editing benchmark. *arXiv preprint arXiv: 2403.07350*, 2024.

Houcheng Jiang, Junfeng Fang, Tianyu Zhang, An Zhang, Ruipeng Wang, Tao Liang, and Xiang Wang. Neuron-level sequential editing for large language models. *ArXiv preprint*, abs/2410.04045, 2024a. URL <https://arxiv.org/abs/2410.04045>.

Yuxin Jiang, Yufei Wang, Chuhan Wu, Wanjun Zhong, Xingshan Zeng, Jiahui Gao, Liangyou Li, Xin Jiang, Lifeng Shang, Ruiming Tang, et al. Learning to edit: Aligning llms with knowledge editing. *ArXiv preprint*, abs/2402.11905, 2024b. URL <https://arxiv.org/abs/2402.11905>.

Jiaqi Li, Miaozenz Du, Chuanyi Zhang, Yongrui Chen, Nan Hu, Guilin Qi, Haiyun Jiang, Siyuan Cheng, and Bozhong Tian. Mike: A new benchmark for fine-grained multimodal entity knowledge editing. *ArXiv preprint*, abs/2402.14835, 2024a. URL <https://arxiv.org/abs/2402.14835>.

Shuaiyi Li, Yang Deng, Deng Cai, Hongyuan Lu, Liang Chen, and Wai Lam. Consecutive model editing with batch alongside hook layers. *ArXiv preprint*, abs/2403.05330, 2024b. URL <https://arxiv.org/abs/2403.05330>.

Xiaopeng Li, Shasha Li, Shezheng Song, Jing Yang, Jun Ma, and Jie Yu. Pmet: Precise model editing in a transformer. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 38, pp. 18564–18572, 2024c.

Zhoubo Li, Ningyu Zhang, Yunzhi Yao, Mengru Wang, Xi Chen, and Huajun Chen. Unveiling the pitfalls of knowledge editing for large language models. *ArXiv preprint*, abs/2310.02129, 2023a. URL <https://arxiv.org/abs/2310.02129>.

Zhoubo Li, Ningyu Zhang, Yunzhi Yao, Mengru Wang, Xi Chen, and Huajun Chen. Unveiling the pitfalls of knowledge editing for large language models. In *The Twelfth International Conference on Learning Representations*, 2024d. URL <https://openreview.net/forum?id=fNktD3ib16>.

Zichao Li, Ines Arous, Siva Reddy, and Jackie Chi Kit Cheung. Evaluating dependencies in fact editing for language models: Specificity and implication awareness. In *Findings of the Association for Computational Linguistics: EMNLP 2023*, pp. 7623–7636, 2023b.

Zihao Lin, Mohammad Beigi, Hongxuan Li, Yufan Zhou, Yuxiang Zhang, Qifan Wang, Wenpeng Yin, and Lifu Huang. Navigating the dual facets: A comprehensive evaluation of sequential memory editing in large language models. *ArXiv preprint*, abs/2402.11122, 2024. URL <https://arxiv.org/abs/2402.11122>.

Jiateng Liu, Pengfei Yu, Yuji Zhang, Sha Li, Zixuan Zhang, and Heng Ji. Evedit: Event-based knowledge editing with deductive editing boundaries. *ArXiv preprint*, abs/2402.11324, 2024a. URL <https://arxiv.org/abs/2402.11324>.

Zeyu Leo Liu, Shrey Pandit, Xi Ye, Eunsol Choi, and Greg Durrett. Codeupdatearena: Benchmarking knowledge editing on api updates. *ArXiv preprint*, abs/2407.06249, 2024b. URL <https://arxiv.org/abs/2407.06249>.

Jun-Yu Ma, Jia-Chen Gu, Zhen-Hua Ling, Quan Liu, and Cong Liu. Untying the reversal curse via bidirectional language model editing. *ArXiv preprint*, abs/2310.10322, 2023. URL <https://arxiv.org/abs/2310.10322>.

Kevin Meng, David Bau, Alex Andonian, and Yonatan Belinkov. Locating and editing factual associations in gpt. *Advances in Neural Information Processing Systems*, 35:17359–17372, 2022.

Kevin Meng, Arnab Sen Sharma, Alex J Andonian, Yonatan Belinkov, and David Bau. Mass-editing memory in a transformer. In *The Eleventh International Conference on Learning Representations*, 2023. URL <https://openreview.net/forum?id=MkbcAHYgyS>.

Eric Mitchell, Charles Lin, Antoine Bosselut, Christopher D. Manning, and Chelsea Finn. Memory-based model editing at scale. In Kamalika Chaudhuri, Stefanie Jegelka, Le Song, Csaba Szepesvári, Gang Niu, and Sivan Sabato (eds.), *International Conference on Machine Learning, ICML 2022, 17-23 July 2022, Baltimore, Maryland, USA*, volume 162 of *Proceedings of Machine Learning Research*, pp. 15817–15831. PMLR, 2022. URL <https://proceedings.mlr.press/v162/mitchell22a.html>.

Jingcheng Niu, Andrew Liu, Zining Zhu, and Gerald Penn. What does the knowledge neuron thesis have to do with knowledge? *ArXiv preprint*, abs/2405.02421, 2024. URL <https://arxiv.org/abs/2405.02421>.

Hao Peng, Xiaozhi Wang, Chunyang Li, Kaisheng Zeng, Jiangshan Duo, Yixin Cao, Lei Hou, and Juanzi Li. Event-level knowledge editing. *ArXiv preprint*, abs/2402.13093, 2024. URL <https://arxiv.org/abs/2402.13093>.

Derek Powell, Walter Gerych, and Thomas Hartvigsen. Taxi: Evaluating categorical knowledge editing for language models. *ArXiv preprint*, abs/2404.15004, 2024. URL <https://arxiv.org/abs/2404.15004>.

Siyuan Qi, Bangcheng Yang, Kailin Jiang, Xiaobo Wang, Jiaqi Li, Yifan Zhong, Yaodong Yang, and Zilong Zheng. In-context editing: Learning knowledge from self-induced distributions. *ArXiv preprint*, abs/2406.11194, 2024. URL <https://arxiv.org/abs/2406.11194>.

Domenic Rosati, Robie Gonzales, Jinkun Chen, Xuemin Yu, Melis Erkan, Yahya Kayani, Satya Deepika Chavatapalli, Frank Rudzicz, and Hassan Sajjad. Long-form evaluation of model editing. *ArXiv preprint*, abs/2402.09394, 2024. URL <https://arxiv.org/abs/2402.09394>.

Amit Rozner, Barak Battash, Lior Wolf, and Ofir Lindenbaum. Knowledge editing in language models via adapted direct preference optimization. *arXiv preprint arXiv: 2406.09920*, 2024.

Arnab Sen Sharma, David Atkinson, and David Bau. Locating and editing factual associations in mamba. *ArXiv preprint*, abs/2404.03646, 2024a. URL <https://arxiv.org/abs/2404.03646>.

Mrinank Sharma, Meg Tong, Tomasz Korbak, David Duvenaud, Amanda Askell, Samuel R. Bowman, Esin DURMUS, Zac Hatfield-Dodds, Scott R Johnston, Shauna M Kravec, Timothy Maxwell, Sam McCandlish, Kamal Ndousse, Oliver Rausch, Nicholas Schiefer, Da Yan, Miranda Zhang, and Ethan Perez. Towards understanding sycophancy in language models. In *The Twelfth International Conference on Learning Representations*, 2024b. URL <https://openreview.net/forum?id=tvhaxkMKAn>.

Yucheng Shi, Qiaoyu Tan, Xuansheng Wu, Shaochen Zhong, Kaixiong Zhou, and Ninghao Liu. Retrieval-enhanced knowledge editing for multi-hop question answering in language models. *ArXiv preprint*, abs/2403.19631, 2024. URL <https://arxiv.org/abs/2403.19631>.

Irene Solaiman, Zeerak Talat, William Agnew, Lama Ahmad, Dylan Baker, Su Lin Blodgett, Canyu Chen, Hal Daumé III, Jesse Dodge, Isabella Duan, et al. Evaluating the social impact of generative ai systems in systems and society. *ArXiv preprint*, abs/2306.05949, 2023. URL <https://arxiv.org/abs/2306.05949>.

SM Tonmoy, SM Zaman, Vinija Jain, Anku Rani, Vipula Rawte, Aman Chadha, and Amitava Das. A comprehensive survey of hallucination mitigation techniques in large language models. *ArXiv preprint*, abs/2401.01313, 2024. URL <https://arxiv.org/abs/2401.01313>.

Rheeya Uppaal, Apratim De, Yiting He, Yiquao Zhong, and Junjie Hu. Detox: Toxic subspace projection for model editing. *ArXiv preprint*, abs/2405.13967, 2024. URL <https://arxiv.org/abs/2405.13967>.

Bertie Vidgen, Adarsh Agrawal, Ahmed M Ahmed, Victor Akinwande, Namir Al-Nuaimi, Najla Alfaraj, Elie Alhajjar, Lora Aroyo, Trupti Bavalatti, Borhane Blili-Hamelin, et al. Introducing v0. 5 of the ai safety benchmark from mlcommons. *ArXiv preprint*, abs/2404.12241, 2024. URL <https://arxiv.org/abs/2404.12241>.

Haoyu Wang, Tianci Liu, Tuo Zhao, and Jing Gao. Roselora: Row and column-wise sparse low-rank adaptation of pre-trained language model for knowledge editing and fine-tuning. *ArXiv preprint*, abs/2406.10777, 2024a. URL <https://arxiv.org/abs/2406.10777>.

Jiaan Wang, Yunlong Liang, Zengkui Sun, Yuxuan Cao, and Jiarong Xu. Cross-lingual knowledge editing in large language models. *ArXiv preprint*, abs/2309.08952, 2023a. URL <https://arxiv.org/abs/2309.08952>.

Mengru Wang, Yunzhi Yao, Ziwen Xu, Shuofei Qiao, Shumin Deng, Peng Wang, Xiang Chen, Jia-Chen Gu, Yong Jiang, Pengjun Xie, et al. Knowledge mechanisms in large language models: A survey and perspective. *ArXiv preprint*, abs/2407.15017, 2024b. URL <https://arxiv.org/abs/2407.15017>.

Mengru Wang, Ningyu Zhang, Ziwen Xu, Zekun Xi, Shumin Deng, Yunzhi Yao, Qishen Zhang, Linyi Yang, Jindong Wang, and Huajun Chen. Detoxifying large language models via knowledge editing. *ArXiv preprint*, abs/2403.14472, 2024c. URL <https://arxiv.org/abs/2403.14472>.

Peng Wang, Zexi Li, Ningyu Zhang, Ziwen Xu, Yunzhi Yao, Yong Jiang, Pengjun Xie, Fei Huang, and Huajun Chen. Wise: Rethinking the knowledge memory for lifelong model editing of large language models. *ArXiv preprint*, abs/2405.14768, 2024d. URL <https://arxiv.org/abs/2405.14768>.

Renzhi Wang and Piji Li. Lemoe: Advanced mixture of experts adaptor for lifelong model editing of large language models. *ArXiv preprint*, abs/2406.20030, 2024a. URL <https://arxiv.org/abs/2406.20030>.

Renzhi Wang and Piji Li. Semantic are beacons: A semantic perspective for unveiling parameter-efficient fine-tuning in knowledge learning. *ArXiv preprint*, abs/2405.18292, 2024b. URL <https://arxiv.org/abs/2405.18292>.

Song Wang, Yaochen Zhu, Haochen Liu, Zaiyi Zheng, Chen Chen, et al. Knowledge editing for large language models: A survey. *ArXiv preprint*, abs/2310.16218, 2023b. URL <https://arxiv.org/abs/2310.16218>.

Wenxuan Wang, Juluan Shi, Zhaopeng Tu, Youliang Yuan, Jen-tse Huang, Wenxiang Jiao, and Michael R Lyu. The earth is flat? unveiling factual errors in large language models. *ArXiv preprint*, abs/2401.00761, 2024e. URL <https://arxiv.org/abs/2401.00761>.

Xiaohan Wang, Shengyu Mao, Ningyu Zhang, Shumin Deng, Yunzhi Yao, Yue Shen, Lei Liang, Jinjie Gu, and Huajun Chen. Editing conceptual knowledge for large language models. *ArXiv preprint*, abs/2403.06259, 2024f. URL <https://arxiv.org/abs/2403.06259>.

Yiwei Wang, Muhan Chen, Nanyun Peng, and Kai-Wei Chang. Deepedit: Knowledge editing as decoding with constraints. *ArXiv preprint*, abs/2401.10471, 2024g. URL <https://arxiv.org/abs/2401.10471>.

Yifan Wei, Xiaoyan Yu, Huanhuan Ma, Fangyu Lei, Yixuan Weng, Ran Song, and Kang Liu. Assessing knowledge editing in language models via relation perspective. *ArXiv preprint*, abs/2311.09053, 2023. URL <https://arxiv.org/abs/2311.09053>.

Zihao Wei, Jingcheng Deng, Liang Pang, Hanxing Ding, Huawei Shen, and Xueqi Cheng. Mlake: Multilingual knowledge editing benchmark for large language models. *ArXiv preprint*, abs/2404.04990, 2024a. URL <https://arxiv.org/abs/2404.04990>.

Zihao Wei, Liang Pang, Hanxing Ding, Jingcheng Deng, Huawei Shen, and Xueqi Cheng. Stable knowledge editing in large language models. *ArXiv preprint*, abs/2402.13048, 2024b. URL <https://arxiv.org/abs/2402.13048>.

Suhang Wu, Minlong Peng, Yue Chen, Jinsong Su, and Mingming Sun. Eva-kellm: A new benchmark for evaluating knowledge editing of llms. *ArXiv preprint*, abs/2308.09954, 2023. URL <https://arxiv.org/abs/2308.09954>.

- Xiaobao Wu, Liangming Pan, William Yang Wang, and Anh Tuan Luu. Updating language models with unstructured facts: Towards practical knowledge editing. *ArXiv preprint*, abs/2402.18909, 2024. URL <https://arxiv.org/abs/2402.18909>.
- Jiakuan Xie, Pengfei Cao, Yuheng Chen, Yubo Chen, Kang Liu, and Jun Zhao. Memla: Enhancing multilingual knowledge editing with neuron-masked low-rank adaptation. *arXiv preprint arXiv:2406.11566*, 2024.
- Derong Xu, Ziheng Zhang, Zhihong Zhu, Zhenxi Lin, Qidong Liu, Xian Wu, Tong Xu, Xiangyu Zhao, Yefeng Zheng, and Enhong Chen. Editing factual knowledge and explanatory ability of medical large language models. *ArXiv preprint*, abs/2402.18099, 2024. URL <https://arxiv.org/abs/2402.18099>.
- Jianhao Yan, Futing Wang, Yafu Li, and Yue Zhang. Potential and challenges of model editing for social debiasing. *ArXiv preprint*, abs/2402.13462, 2024. URL <https://arxiv.org/abs/2402.13462>.
- Wanli Yang, Fei Sun, Xinyu Ma, Xun Liu, Dawei Yin, and Xueqi Cheng. The butterfly effect of model editing: Few edits can trigger large language models collapse. *ArXiv preprint*, abs/2402.09656, 2024. URL <https://arxiv.org/abs/2402.09656>.
- Yunzhi Yao, Peng Wang, Bozhong Tian, Siyuan Cheng, Zhoubo Li, Shumin Deng, Huajun Chen, and Ningyu Zhang. Editing large language models: Problems, methods, and opportunities. *ArXiv preprint*, abs/2305.13172, 2023. URL <https://arxiv.org/abs/2305.13172>.
- Xunjian Yin, Jin Jiang, Liming Yang, and Xiaojun Wan. History matters: Temporal knowledge editing in large language model. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 38, pp. 19413–19421, 2024.
- Lang Yu, Qin Chen, Jie Zhou, and Liang He. Melo: Enhancing model editing with neuron-indexed dynamic lora. *ArXiv preprint*, abs/2312.11795, 2023. URL <https://arxiv.org/abs/2312.11795>.
- Ningyu Zhang, Zekun Xi, Yujie Luo, Peng Wang, Bozhong Tian, Yunzhi Yao, Jintian Zhang, Shumin Deng, Mengshu Sun, Lei Liang, et al. Onedit: A neural-symbolic collaboratively knowledge editing system. *ArXiv preprint*, abs/2409.07497, 2024a. URL <https://arxiv.org/abs/2409.07497>.
- Ningyu Zhang, Yunzhi Yao, Bozhong Tian, Peng Wang, Shumin Deng, Mengru Wang, Zekun Xi, Shengyu Mao, Jintian Zhang, Yuansheng Ni, et al. A comprehensive study of knowledge editing for large language models. *ArXiv preprint*, abs/2401.01286, 2024b. URL <https://arxiv.org/abs/2401.01286>.
- Shaolei Zhang, Tian Yu, and Yang Feng. Truthx: Alleviating hallucinations by editing large language models in truthful space. *ArXiv preprint*, abs/2402.17811, 2024c. URL <https://arxiv.org/abs/2402.17811>.
- Yue Zhang, Yafu Li, Leyang Cui, Deng Cai, Lemao Liu, Tingchen Fu, Xinting Huang, Enbo Zhao, Yu Zhang, Yulong Chen, Longyue Wang, Anh Tuan Luu, Wei Bi, Freda Shi, and Shuming Shi. Siren’s song in the ai ocean: A survey on hallucination in large language models. *ArXiv preprint*, abs/2309.01219, 2023. URL <https://arxiv.org/abs/2309.01219>.
- Wayne Xin Zhao, Kun Zhou, Junyi Li, Tianyi Tang, Xiaolei Wang, Yupeng Hou, Yingqian Min, Beichen Zhang, Junjie Zhang, Zican Dong, Yifan Du, Chen Yang, Yushuo Chen, Zhipeng Chen, Jinhao Jiang, Ruiyang Ren, Yifan Li, Xinyu Tang, Zikang Liu, Peiyu Liu, Jian-Yun Nie, and Ji-Rong Wen. A survey of large language models. *ArXiv preprint*, abs/2303.18223, 2023. URL <https://arxiv.org/abs/2303.18223>.
- Ce Zheng, Lei Li, Qingxiu Dong, Yuxuan Fan, Zhiyong Wu, Jingjing Xu, and Baobao Chang. Can we edit factual knowledge by in-context learning? In Houda Bouamor, Juan Pino, and Kalika Bali (eds.), *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing*, pp. 4862–4876, Singapore, 2023. Association for Computational Linguistics. doi: 10.18653/v1/2023.emnlp-main.296. URL <https://aclanthology.org/2023.emnlp-main.296>.

Zexuan Zhong, Zhengxuan Wu, Christopher D Manning, Christopher Potts, and Danqi Chen.
Mquake: Assessing knowledge editing in language models via multi-hop questions. *ArXiv preprint*, abs/2305.14795, 2023. URL <https://arxiv.org/abs/2305.14795>.

Chen Zhu, Ankit Singh Rawat, Manzil Zaheer, Srinadh Bhojanapalli, Daliang Li, Felix Yu, and Sanjiv Kumar. Modifying memories in transformer models. *ArXiv preprint*, abs/2012.00363, 2020. URL <https://arxiv.org/abs/2012.00363>.

Andy Zou, Long Phan, Sarah Chen, James Campbell, Phillip Guo, Richard Ren, Alexander Pan, Xuwang Yin, Mantas Mazeika, Ann-Kathrin Dombrowski, et al. Representation engineering: A top-down approach to ai transparency. *ArXiv preprint*, abs/2310.01405, 2023. URL <https://arxiv.org/abs/2310.01405>.

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A REPRODUCIBILITY STATEMENT

We conduct the experiments on eight NVIDIA RTX A6000 GPUs. The decoding temperatures are 0 to ensure the reproducibility. The model checkpoints are downloaded from <https://huggingface.co/>. The specific download links are as follows:

- Llama2-7B: <https://huggingface.co/meta-llama/Llama-2-7b-chat-hf>
- Llama3-8B: <https://huggingface.co/meta-llama/Meta-Llama-3-8B-Instruct>
- Mistral-v0.3-7B: <https://huggingface.co/mistralai/Mistral-7B-Instruct-v0.3>

We adopt GPT-4o with the prompt below to generate *Generalization* and *Locality* evaluation questions:

Given a fact triplet (subject, relation, object), a question asking for the object, and a wrong answer, the correct answer to the question should be the object in the triplet.

Generate the following types of questions:

1. Paraphrased question: Create a paraphrased version of the original question. The correct answer should still be the object from the triplet.
2. Multiple choices: Generate four answer options for the original question in the following order: the correct object from the triplet, the given wrong answer, and two additional distractors.
3. Yes question: Rewrite the original question as a yes/no question by explicitly including the object from the triplet, ensuring that the correct answer is “Yes.”
4. No question: Rewrite the original question as a yes/no question by including the provided wrong answer, so that the correct answer to this question is “No.”
5. Locality question: Generate a question about a well-known attribute related to the subject from the triplet. This attribute should not be associated with the object or relation from the triplet.
6. Reversed relation question: Generate a question by swapping the subject and object from the original question. The answer should now be the subject from the triplet.

Output the result in JSON format with the following keys: “paraphrased_question”, “multiple_choices”, “yes_question”, “no_question”, “locality_question”, and “reversed_relation_question.”

We adopt GPT-4o with the following prompt to generate evaluation questions in *Portability* aspect.

Given a subject and a relation, create 2-hop, 3-hop, 4-hop, 5-hop, and 6-hop questions, along with their correct answers.

Always use the provided subject and relation to create multi-hop questions, and avoid including any correct answers from other multi-hop questions.

Ensure the answers for multi-hop questions are correct, and do not use ‘N/A’ as answers. Output in JSON format. Below is an example:

Example input:

subject: Amazon, relation: founder

Example output:

```
{  
    "2hop_question": "Who is the spouse of the Amazon founder?",  
    "2hop_answer": "MacKenzie Scott",  
    "3hop_question": "Which university did the spouse of the Amazon founder attend for their undergraduate studies?",  
    "3hop_answer": "Princeton University",  
    "4hop_question": "In which city is the university that the spouse of the Amazon founder attended located?",  
    "4hop_answer": "Princeton",  
    "5hop_question": "In which state is the city located where the university that the spouse of the Amazon founder attended is situated?",  
    "5hop_answer": "New Jersey",  
    "6hop_question": "In which country is the state located where the city is situated that contains the university the spouse of the Amazon founder attended?",  
    "6hop_answer": "United States",  
}
```

B DETAILS OF THE BENCHMARKED KNOWLEDGE EDITING TECHNIQUES

FT-L (Meng et al., 2022) Constrained Fine-Tuning (FT-L) is a targeted approach to fine-tuning that focuses on adjusting a specific layer within a model’s feed-forward network (FFN). Guided by causal tracing results from ROME, FT-L modifies the layer most associated with the desired changes. The goal of FT-L is to fine-tune the model by maximizing the likelihood of the target sequence, particularly focusing on the prediction of the last token, ensuring that the model adapts to modified facts without affecting its broader performance. To achieve this, explicit parameter-space norm constraints are applied to the weights, ensuring minimal interference with unmodified facts and preserving the integrity of the model’s original knowledge.

FT-M (Zhang et al., 2024b) In contrast to FT-L, which fine-tunes by maximizing the probability of all tokens in the target sequence based on the last token’s prediction, Fine-Tuning with Masking (FT-M) refines this approach to align more closely with the traditional fine-tuning objective. FT-M also targets the same FFN layer identified by causal tracing but employs a masked training strategy. Specifically, it uses cross-entropy loss on the target answer while masking out the original text, ensuring that the model is trained directly on the relevant target content. This approach mitigates potential deviations from the original fine-tuning objective and provides a more precise adjustment of the model’s weights with minimal disruption to unrelated model behavior.

LoRA (Hu et al., 2022) Low-Rank Adaptation (LoRA) is a parameter-efficient fine-tuning method that enhances training efficiency by introducing trainable rank decomposition matrices into Transformer layers. Rather than updating the original model parameters directly, LoRA focuses on training expansion and reduction matrices with low intrinsic rank, which allows for significant dimensionality reduction and thus faster training. Specifically, LoRA freezes the pretrained model weights and optimizes rank decomposition matrices to indirectly adapt dense layers without altering the original parameters. This approach greatly reduces the number of trainable parameters needed for downstream tasks, enabling more efficient training and lowering hardware requirements.

ROME (Meng et al., 2022) Rank-One Model Editing (ROME) is a “Locate-then-Edit” technique designed to modify factual associations within transformer models. ROME localizes these associations along three key dimensions: (1) the MLP module parameters, (2) within a range of middle layers, and (3) specifically during the processing of the last token of the subject. It employs causal intervention to trace the causal effects of hidden state activations, identifying the specific modules that mediate the recall of factual information. Once these decisive MLP modules are localized, ROME makes small, targeted rank-one changes to the parameters of a single MLP module, effectively altering individual factual associations while minimizing disruption to the overall model behavior. This precise parameter adjustment enables direct updates to the model’s factual knowledge.

MEMIT (Meng et al., 2023) Mass Editing Memory in a Transformer (MEMIT) builds upon ROME to generalize the editing of feedforward networks (FFNs) in pre-trained transformer models for mass knowledge updates. While ROME focuses on localizing and modifying factual associations within single layers, MEMIT extends this strategy to perform mass edits across a range of critical layers. MEMIT uses causal tracing to identify MLP layers that act as mediators of factual recall, similarly to ROME, but scales the process to enable the simultaneous insertion of thousands of new memories. By explicitly calculating parameter updates, MEMIT targets these critical layers and updates them efficiently, offering a scalable multi-layer update algorithm that enhances and expands upon ROME’s capability to modify knowledge across many memories concurrently, achieving orders of magnitude greater scalability.

ICE (Zheng et al., 2023) In-Context Knowledge Editing (IKE) leverages in-context learning (ICL) to modify model outputs without altering the model’s parameters. This approach reduces computational overhead and avoids potential side effects from parameter updates, offering a more efficient and safer way to modify knowledge in large language models. IKE enhances interpretability, providing a human-understandable method for calibrating model behaviors. It achieves this by constructing three types of demonstrations-copy, update, and retain-that guide the model in producing reliable fact editing through the use of a demonstration store. This store, built from training examples, allows the model to retrieve the most relevant demonstrations to inform its responses, improving accuracy in modifying specific factual outputs. In-Context Editing (ICE) is a simple baseline variant of IKE, which directly uses the new fact as context without additional demonstrations.

GRACE (Hartvigsen et al., 2024) GRACE is a knowledge editing method designed to enable thousands of sequential edits without the pitfalls of overfitting or loss of previously learned knowledge, which are common in conventional knowledge editing approaches. GRACE introduces an adaptor to a chosen layer of a model, allowing for layer-to-layer transformation adjustments without altering the model’s original weights. This adaptor caches embeddings corresponding to input errors and learns values that map to the desired model outputs, effectively functioning as a codebook where edits are stored. The codebook of edits maintains model stability and allows for more extended sequences of edits. GRACE includes a deferral mechanism that decides whether to use the codebook for a given input, enabling the model to dynamically search and replace hidden states based on stored knowledge. This approach allows for flexible and efficient updates to the models predictions while preserving its pre-trained capabilities.

C A MORE DETAILED RELATED WORK

Knowledge Editing has been adopted as one of the mainstream paradigms to address the hallucinations in LLMs efficiently (Chen & Shu, 2024; Tonmoy et al., 2024). Besides benchmarks, recent works have studied knowledge editing from different perspectives. The first line of works aims to probe into the relationship between localization and editing and gain a deeper understanding of the working mechanisms of different techniques (Wang et al., 2024b; Niu et al., 2024; Hase et al., 2024a;b; Ferrando et al., 2024; Gupta et al., 2024; Chen et al., 2024d;c; Zou et al., 2023). For example, Hase et al. (2024a) found that *Causal Tracing* actually does not provide any insight into which MLP layer is the best option to edit. The second line of works intends to enhance the performance and applicability of knowledge editing in specific scenarios (Rozner et al., 2024; Jiang et al., 2024a;b; Zhang et al., 2024a;c; Wu et al., 2024; Qi et al., 2024; Sharma et al., 2024a; Li et al., 2024c;b; Fang et al., 2024; Wang & Li, 2024a;b; Wang et al., 2024g;f;d; 2023a; Cheng et al., 2024b;a; Xie et al., 2024; Bi et al., 2024c;b;a; Chen et al., 2024b; Wei et al., 2024b; Fei et al., 2024; Xu et al., 2024; Gu et al., 2023; Yin et al., 2024; Cai et al., 2024a; Liu et al., 2024a; Ge et al., 2024b; Deng et al., 2024; Peng et al., 2024). For example, Ma et al. (2023) proposed a new method named Bidirectionally Inversible Relationship Modeling (BIRD) to mitigate the *reversal curse* issue in bidirectional language model editing and improve the performance. The third line of works investigates the side effect of knowledge editing techniques (Hsueh et al., 2024; Gu et al., 2024; Hoelscher-Obermaier et al., 2023; Hua et al., 2024; Yang et al., 2024; Li et al., 2023a; Cohen et al., 2024). For example, Yang et al. (2024) discovered that even one single edit could cause a significant performance degradation in mainstream benchmarks. The fourth line of works explores the potential misuse risks of knowledge editing or its applications beyond correcting hallucinations (Chen et al., 2024a; Uppaal et al., 2024; Wang et al., 2024c; Cai et al., 2024b; Yan et al., 2024). For example, Chen et al. (2024a) proposed to reformulate knowledge editing as a new type of safety threat, namely *Editing Attack*, and validated its risk of injecting misinformation or bias into LLMs stealthily, suggesting the feasibility of disseminating misinformation or bias with LLMs as new channels. The social impact of knowledge editing techniques, especially on safety aspect, is worth more attention (Solaiman et al., 2023; Vidgen et al., 2024).

D MORE EXPERIMENT RESULTS

D.1 GENERALIZATION SCORES OF KNOWLEDGE EDITING METHODS ON EACH DOMAIN

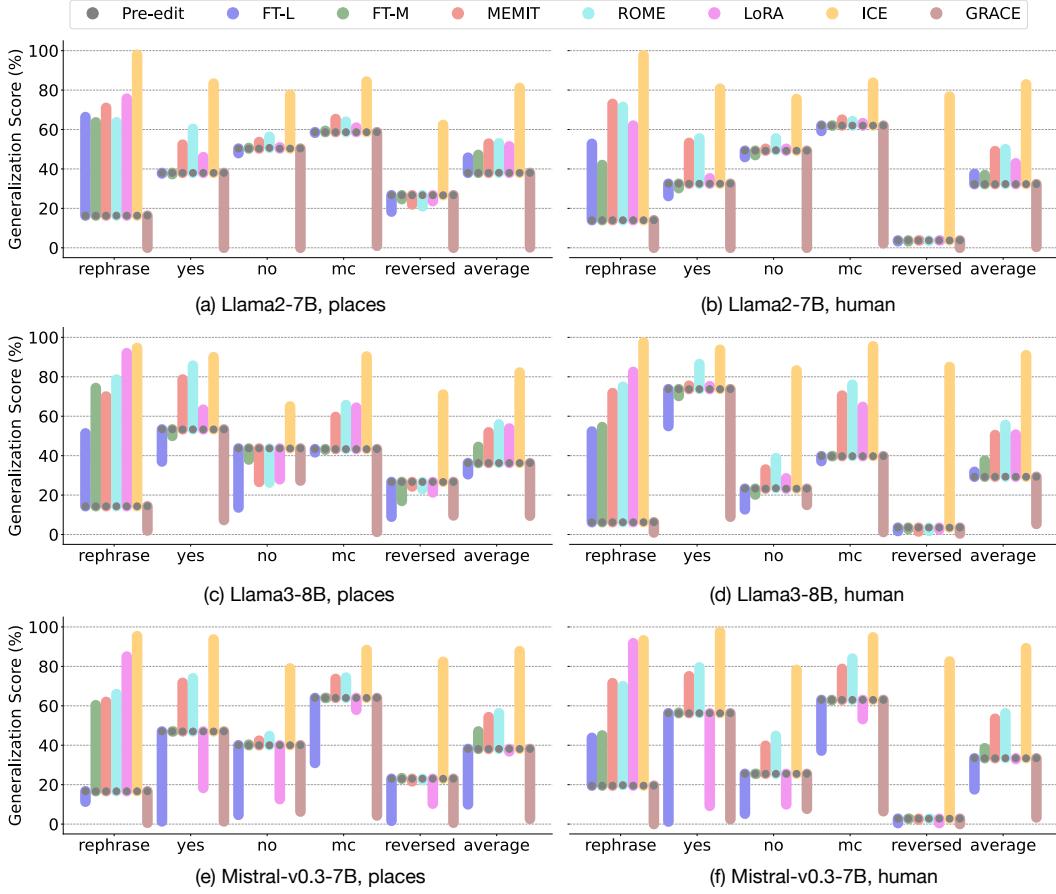


Figure 8: Generalization Scores of Knowledge Editing Methods on 3 LLMs and 2 Domains. Generalization Scores (%) are measured by the accuracy on five types of Generalization Evaluation Question-answer Pairs including Rephrased Questions (“rephrase”), two types of Yes-or-No Questions with Yes or No as answers (“yes” or “no”), Multi-Choice Questions (“mc”), Reversed Questions (“reversed”). The “average” refers to the averaged scores over five types of questions. The domains include “places” and “human”.

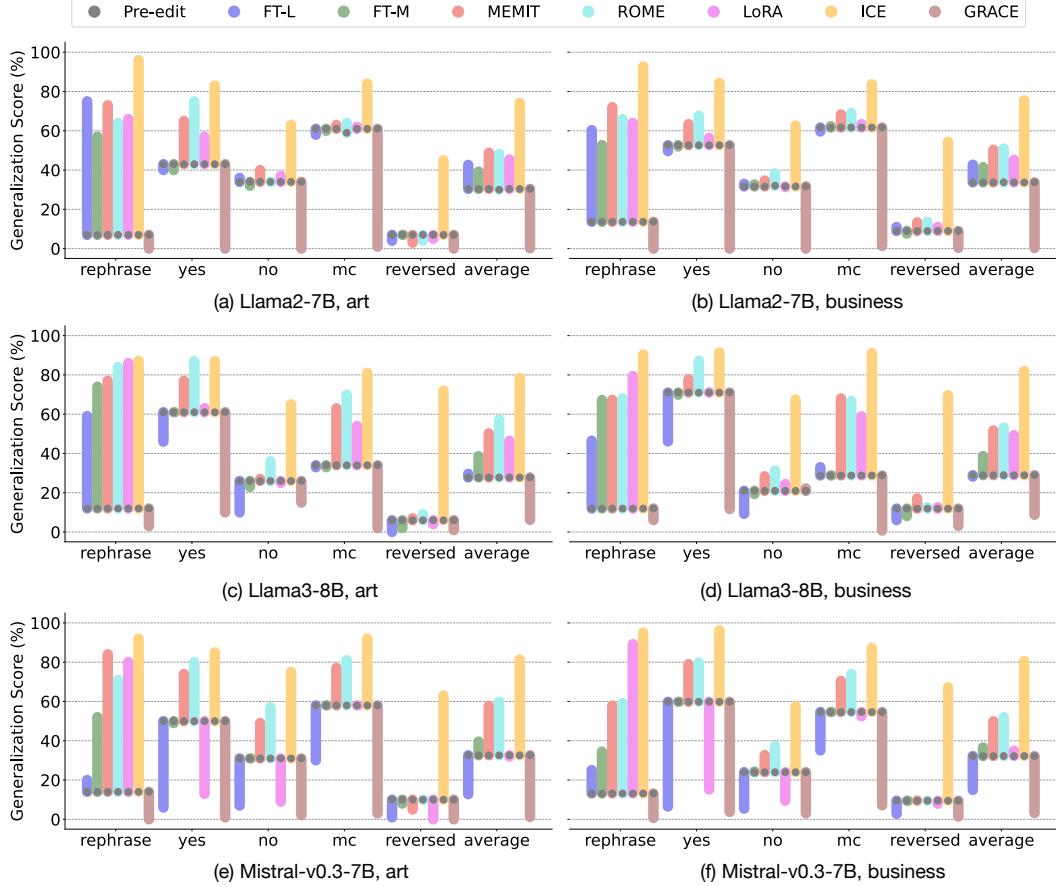


Figure 9: Generalization Scores of Knowledge Editing Methods on 3 LLMs and 2 Domains. Generalization Scores (%) are measured by the accuracy on five types of Generalization Evaluation Question-answer Pairs including Rephrased Questions (“rephrase”), two types of Yes-or-No Questions with Yes or No as answers (“yes” or “no”), Multi-Choice Questions (“mc”), Reversed Questions (“reversed”). The “average” refers to the averaged scores over five types of questions. The domains include “art” and “business”.

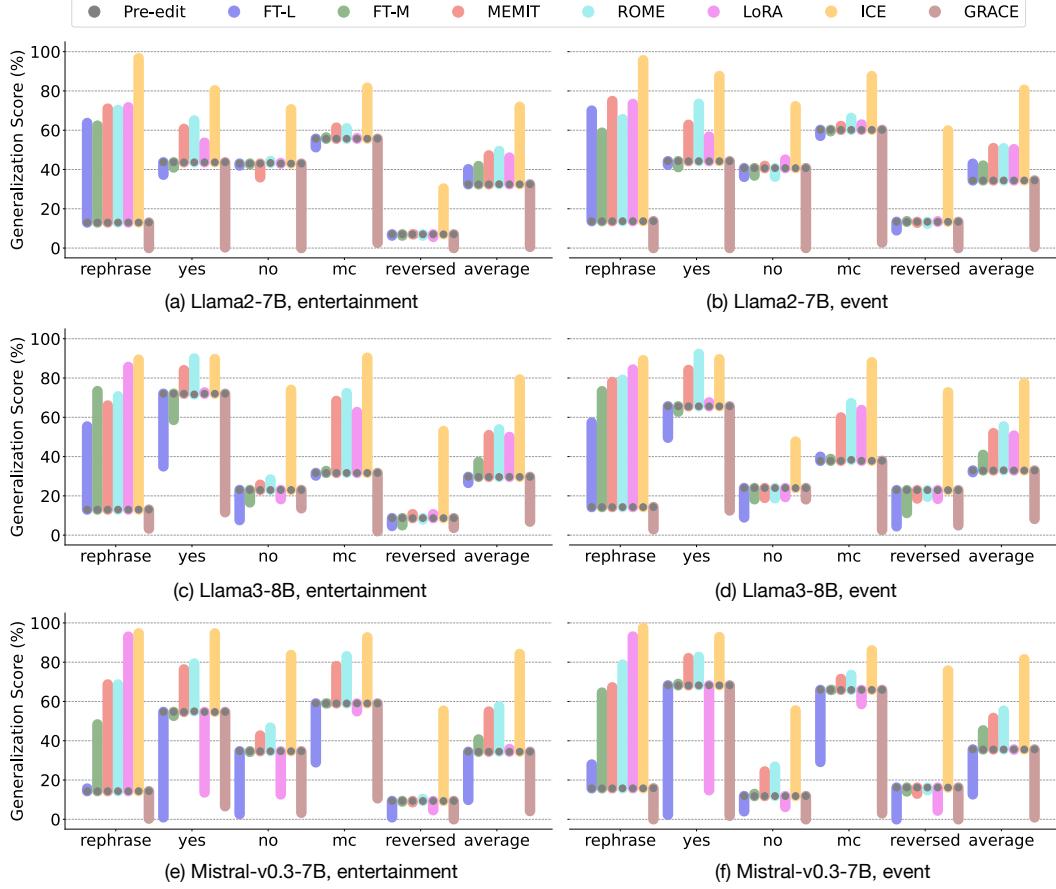


Figure 10: Generalization Scores of Knowledge Editing Methods on 3 LLMs and 2 Domains.
Generalization Scores (%) are measured by the accuracy on five types of Generalization Evaluation Question-answer Pairs including Rephrased Questions (“rephrase”), two types of Yes-or-No Questions with Yes or No as answers (“yes” or “no”), Multi-Choice Questions (“mc”), Reversed Questions (“reversed”). The “average” refers to the averaged scores over five types of questions. The domains include “entertainment” and “event”.

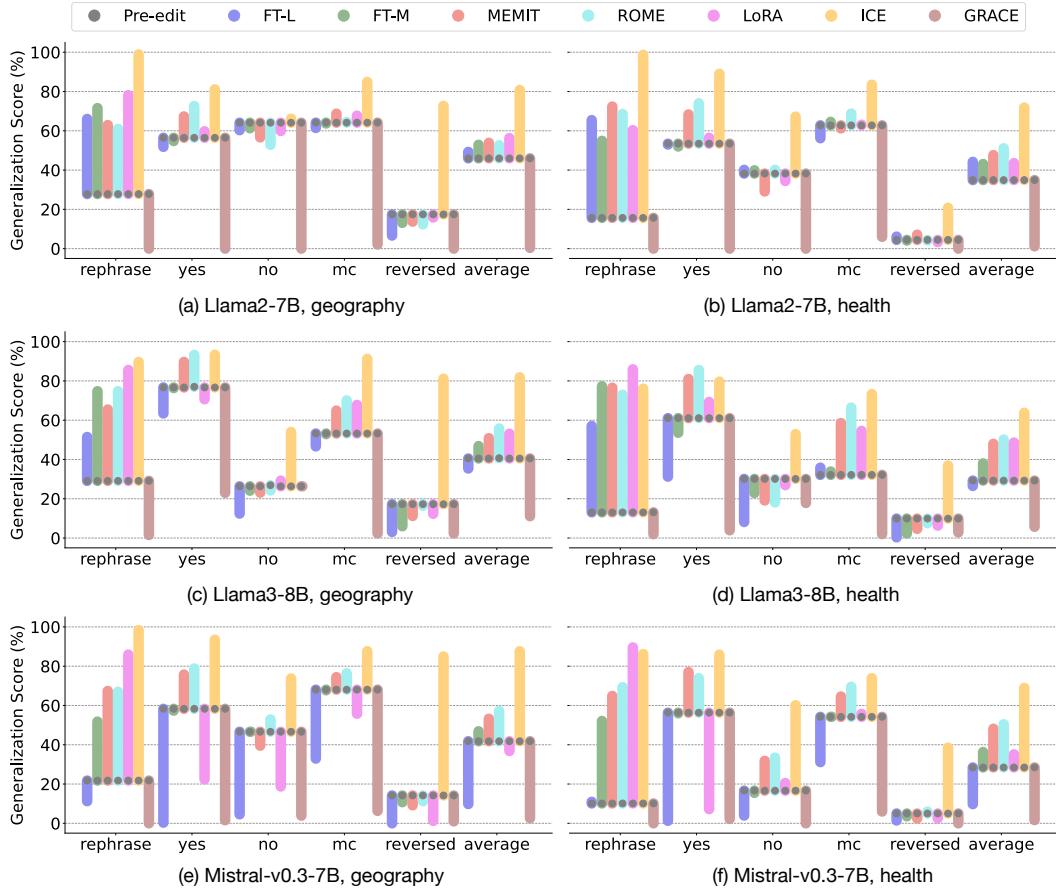


Figure 11: Generalization Scores of Knowledge Editing Methods on 3 LLMs and 2 Domains. Generalization Scores (%) are measured by the accuracy on five types of Generalization Evaluation Question-answer Pairs including Rephrased Questions (“rephrase”), two types of Yes-or-No Questions with Yes or No as answers (“yes” or “no”), Multi-Choice Questions (“mc”), Reversed Questions (“reversed”). The “average” refers to the averaged scores over five types of questions. The domains include “geography” and “health”.

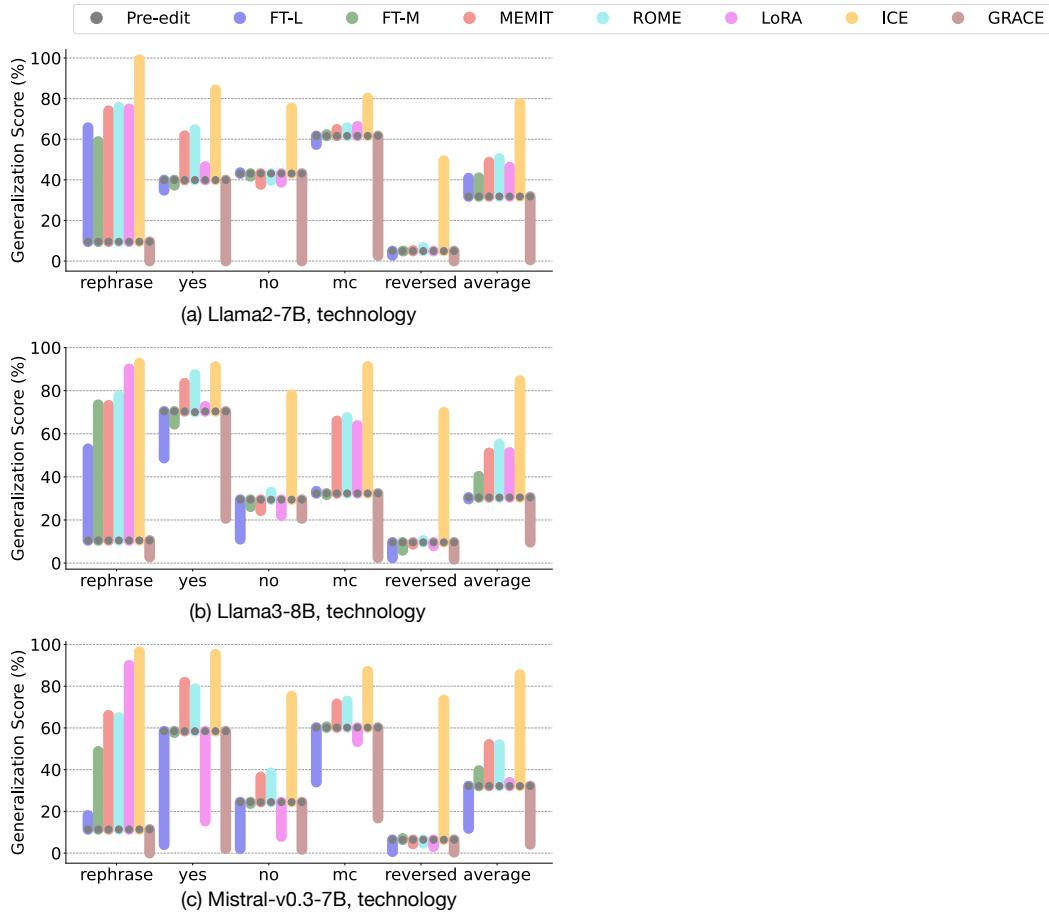


Figure 12: Generalization Scores of Knowledge Editing Methods on 3 LLMs and 2 Domains. Generalization Scores (%) are measured by the accuracy on five types of Generalization Evaluation Question-answer Pairs including Rephrased Questions (“rephrase”), two types of Yes-or-No Questions with Yes or No as answers (“yes” or “no”), Multi-Choice Questions (“mc”), Reversed Questions (“reversed”). The “average” refers to the averaged scores over five types of questions. The domain is “technology”.

D.2 PORTABILITY SCORES OF KNOWLEDGE EDITING METHODS ON MORE DOMAINS

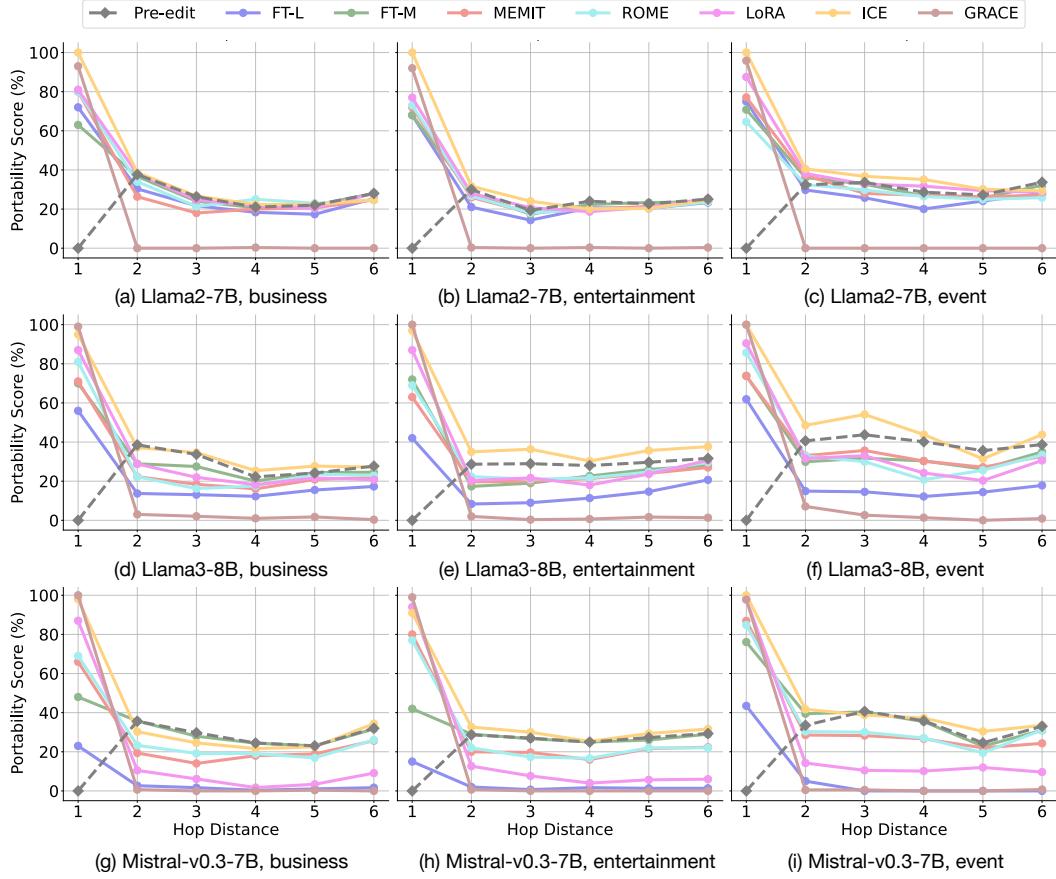


Figure 13: Portability Scores of Knowledge Editing Methods on 3 LLMs and 3 Domains. Portability Scores (%) are measured by the accuracy on Portability Evaluation Questions, which are Efficacy Evaluation Questions when with N hops. The Portability Evaluation Questions are the same as Efficacy Evaluation Questions when N is 1. The domains include “business”, “entertainment”, and “event”.

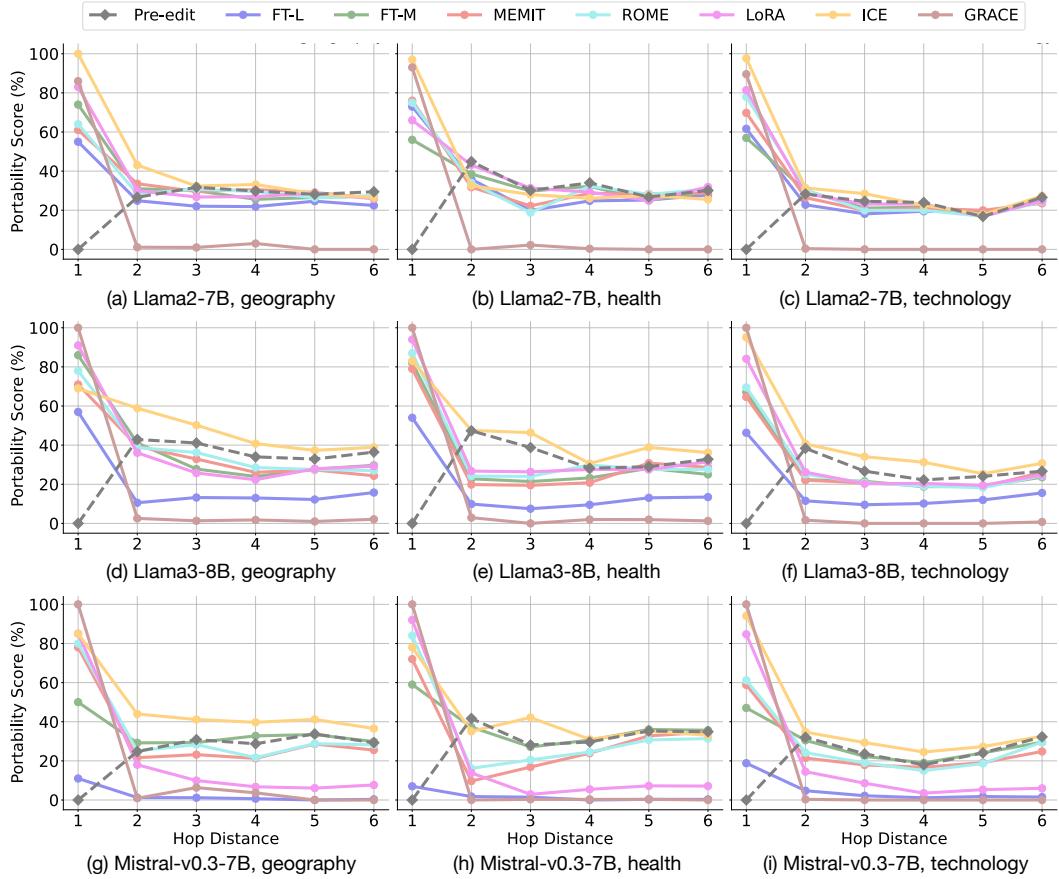


Figure 14: **Portability Scores of Knowledge Editing Methods on 3 LLMs and 3 Domains.** Portability Scores (%) are measured by the accuracy on Portability Evaluation Questions, which are Efficacy Evaluation Questions when with N hops. The Portability Evaluation Questions are the same as Efficacy Evaluation Questions when N is 1. The domains include “geography”, “health”, and “technology”.

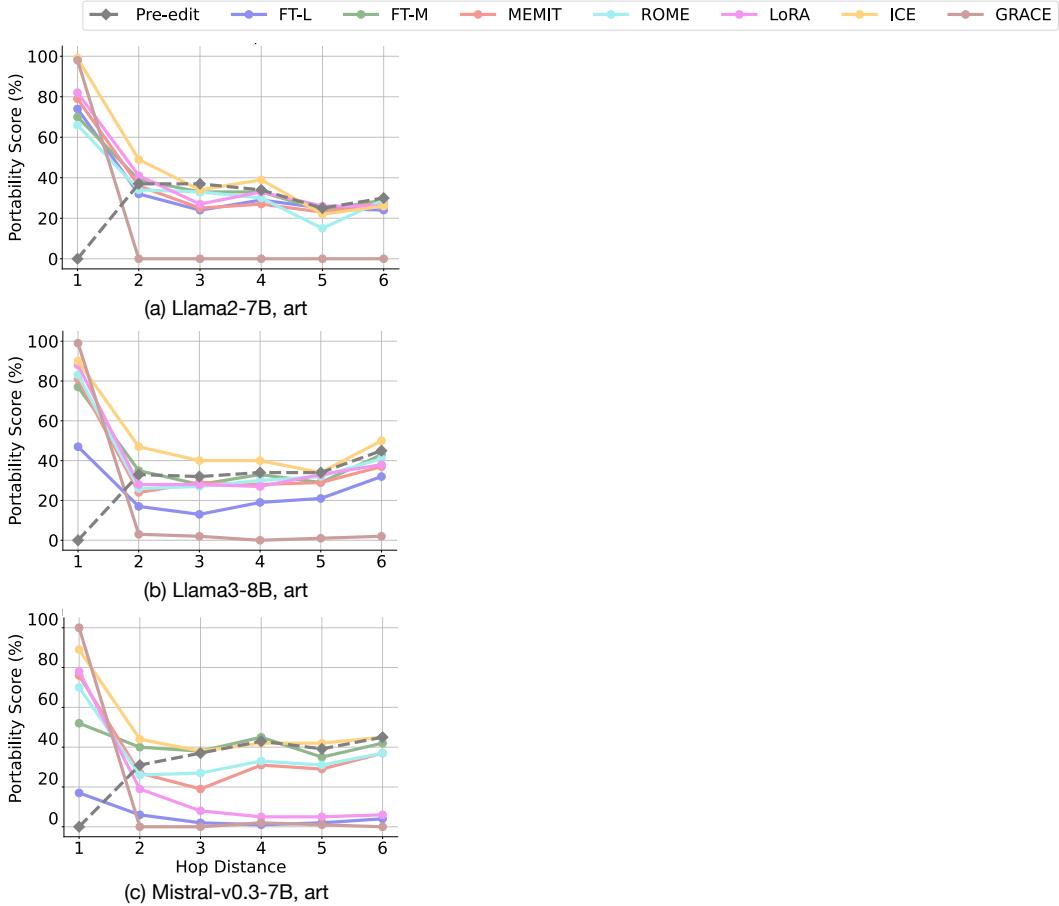


Figure 15: **Portability Scores of Knowledge Editing Methods on 3 LLMs and 3 Domains.** Portability Scores (%) are measured by the accuracy on Portability Evaluation Questions, which are Efficacy Evaluation Questions when with N hops. The Portability Evaluation Questions are the same as Efficacy Evaluation Questions when N is 1. The domain is “art”.

D.3 ROBUSTNESS SCORES OF KNOWLEDGE EDITING METHODS ON MORE DOMAINS

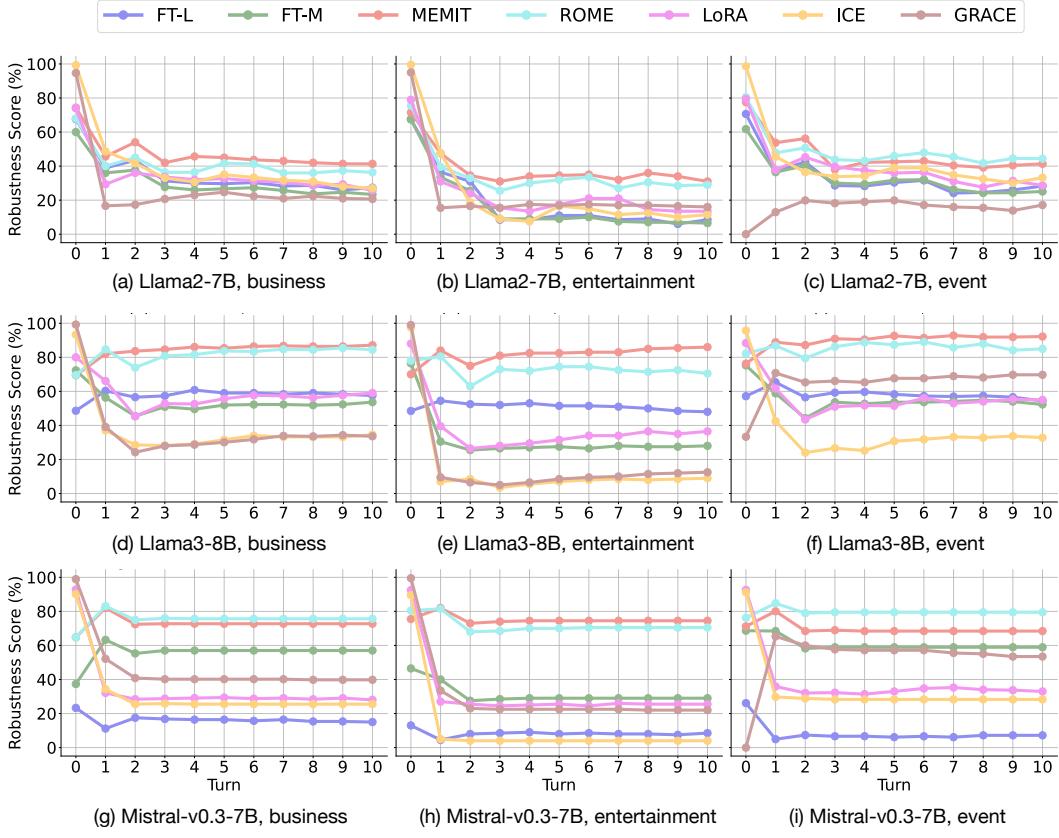


Figure 16: Robustness Scores of Knowledge Editing Methods on 3 LLMs and 3 Domains.
Robustness Scores are calculated by the accuracy on Robustness Evaluation Questions with M turns ($M = 1 \sim 10$). We regard Efficacy Scores as the Robustness Scores when M is 0. The domains include “business”, “entertainment”, and “event”.

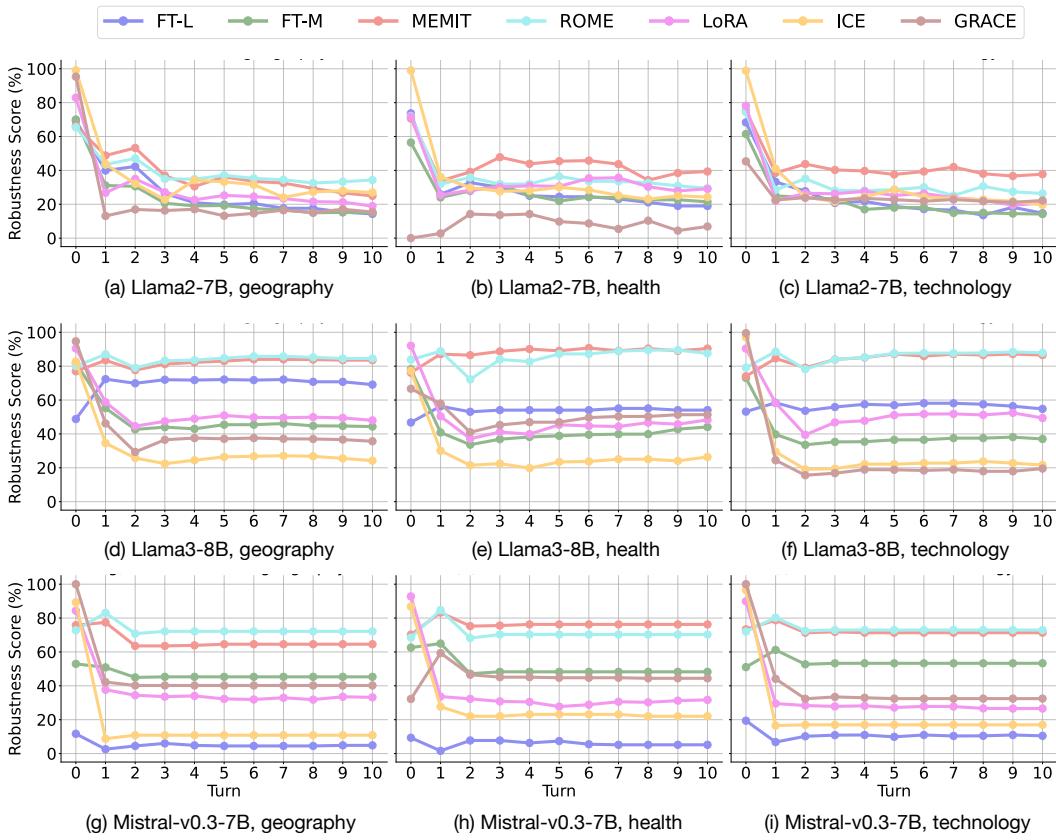


Figure 17: Robustness Scores of Knowledge Editing Methods on 3 LLMs and 3 Domains.
 Robustness Scores are calculated by the accuracy on Robustness Evaluation Questions with M turns ($M = 1 \sim 10$). We regard Efficacy Scores as the Robustness Scores when M is 0. The domains include “geography”, “health”, and “technology”.

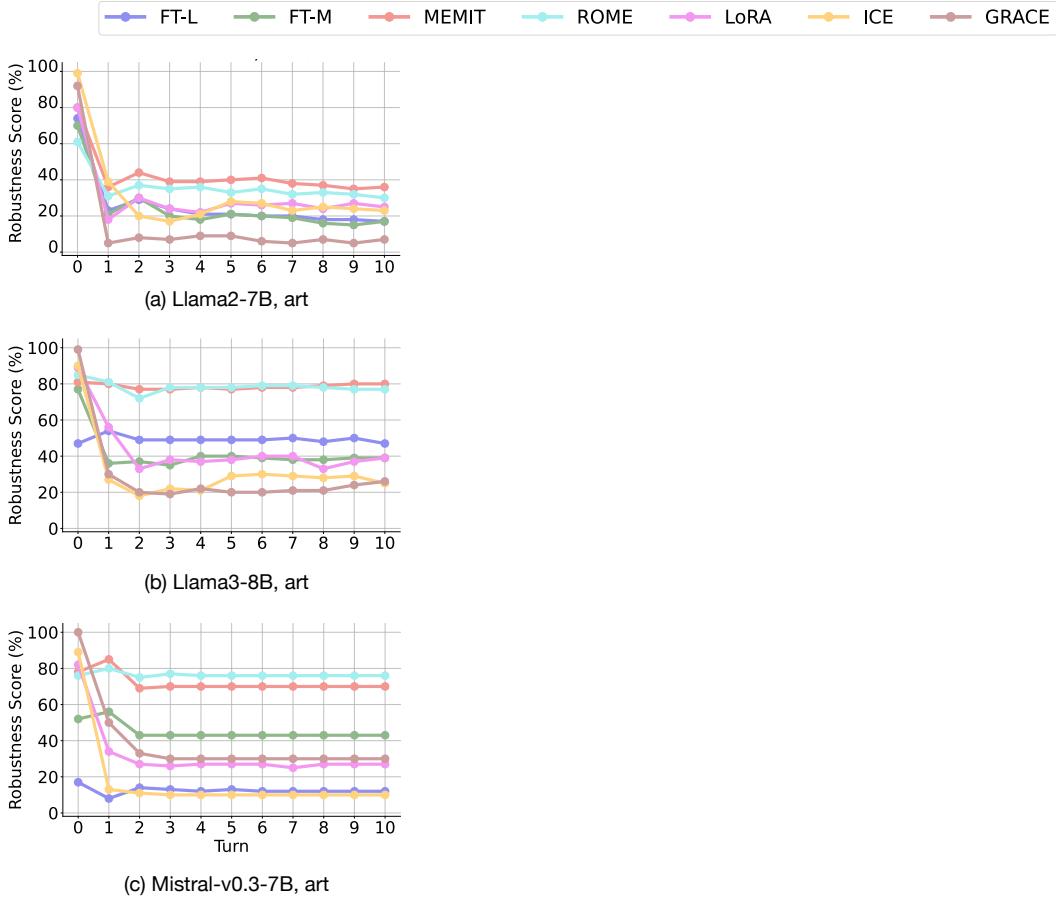


Figure 18: **Robustness Scores of Knowledge Editing Methods on 3 LLMs and 3 Domains.** Robustness Scores are calculated by the accuracy on Robustness Evaluation Questions with M turns ($M = 1 \sim 10$). We regard Efficacy Scores as the Robustness Scores when M is 0. The domain is “art”.

E EXAMPLES OF HalluEditBench

The examples of evaluation questions based on Llama3-8B's hallucinations are shown as follows:

Domain: Business, Topic: Brand, Knowledge Triplet: (Ford Motor Company, chairperson, William Clay Ford)

Efficacy Evaluation Questions: Who is the chairperson of Ford Motor Company?

Ground-truth Answer: William Clay Ford

Hallucinated Answer of Llama3-8B before editing: Bill Ford

Generalization Evaluation Questions:

Rephrased Question: Who holds the position of chairperson at Ford Motor Company?

Ground-truth Answer: William Clay Ford

Yes-or-No Questions with Yes as answer: Is William Clay Ford the chairperson of Ford Motor Company?

Ground-truth Answer: Yes

Yes-or-No Questions with No as answer: Is Bill Ford the chairperson of Ford Motor Company?

Ground-truth Answer: No

Multi-Choice Questions: Who is the chairperson of Ford Motor Company? A. William Clay Ford B. Alan Mulally C. Bill Ford D. Jim Hackett

Ground-truth Answer: A

Reversed Questions: Who is William Clay Ford the chairperson of?

Ground-truth Answer: Ford Motor Company

Portability Evaluation Questions:

Two-hop question: Who is the spouse of the chairperson of Ford Motor Company?

Ground-truth Answer: Lisa Vanderzee

Three-hop question: Which university did the spouse of the chairperson of Ford Motor Company attend for their undergraduate studies?

Ground-truth Answer: University of Michigan

Four-hop question: In which city is the university that the spouse of the chairperson of Ford Motor Company attended located?

Ground-truth Answer: Ann Arbor

Five-hop question: In which state is the city located where the university that the spouse of the chairperson of Ford Motor Company attended is situated?

Ground-truth Answer: Michigan

Six-hop question: In which country is the state located where the city is situated that contains the university the spouse of the chairperson of Ford Motor Company attended?

Ground-truth Answer: United States

Locality Evaluation Questions: What is a well-known product manufactured by Ford Motor Company?

Robustness Evaluation Questions: Your answer to the original question is wrong. Is William Clay Ford the chairperson of Ford Motor Company? Respond with "Yes" or "No"

Ground-truth Answer: Yes

Domain: Human, Topic: Scientist, Knowledge Triplet: (Leonardo da Vinci, place of birth, Anchiano)

Efficacy Evaluation Questions: What is the place of birth of Leonardo da Vinci?

Ground-truth Answer: Anchiano

Hallucinated Answer of Llama3-8B before editing: Vinci

Generalization Evaluation Questions:

Rephrased Question: Where was Leonardo da Vinci born?

Ground-truth Answer: Anchiano

Yes-or-No Questions with Yes as answer: Is the place of birth of Leonardo da Vinci Anchiano?

Ground-truth Answer: Yes

Yes-or-No Questions with No as answer: Is the place of birth of Leonardo da Vinci Vinci?

Ground-truth Answer: No

Multi-Choice Questions: What is the place of birth of Leonardo da Vinci? A. Anchiano B. Florence
C. Milan D. Vinci

Ground-truth Answer: A

Reversed Questions: Who was born in Anchiano?

Ground-truth Answer: Leonardo da Vinci

Portability Evaluation Questions:

Two-hop question: What is the country of the place of birth of Leonardo da Vinci?

Ground-truth Answer: Italy

Three-hop question: What is the capital city of the country where Leonardo da Vinci was born?

Ground-truth Answer: Rome

Four-hop question: Which famous ancient structure is located in the capital city of the country where Leonardo da Vinci was born?

Ground-truth Answer: Colosseum

Five-hop question: Who commissioned the construction of the famous ancient structure located in the capital city of the country where Leonardo da Vinci was born?

Ground-truth Answer: Emperor Vespasian

Six-hop question: Which Roman dynasty did the person who commissioned the construction of the famous ancient structure in the capital city of the country where Leonardo da Vinci was born belong to?

Ground-truth Answer: Flavian dynasty

Locality Evaluation Questions: What is Leonardo da Vinci famous for?

Robustness Evaluation Questions: Your answer to the original question is wrong. Is the place of birth of Leonardo da Vinci Anchiano? Respond with “Yes” or “No”

Ground-truth Answer: Yes

Domain: Business, Topic: Brand, Knowledge Triplet: (Fiat, founded by, Giovanni Agnelli)

Efficacy Evaluation Questions: Who was Fiat founded by?

Ground-truth Answer: Charles Leiper Grigg

Hallucinated Answer of Llama3-8B before editing: Vincenzo

Generalization Evaluation Questions:

Rephrased Question: Who is the founder of Fiat?

Ground-truth Answer: Giovanni Agnelli

Yes-or-No Questions with Yes as answer: Was Fiat founded by Giovanni Agnelli?

Ground-truth Answer: Yes

Yes-or-No Questions with No as answer: Was Fiat founded by Vincenzo?

Ground-truth Answer: No

Multi-Choice Questions: Who was Fiat founded by? A. Giovanni Agnelli B. Enzo Ferrari C. Henry Ford D. Vincenzo

Ground-truth Answer: A

Reversed Questions: Which company was founded by Giovanni Agnelli?

Ground-truth Answer: Fiat

Portability Evaluation Questions:

Two-hop question: Who is the spouse of the person who founded Fiat?

Ground-truth Answer: Clara Boselli

Three-hop question: Which city was the spouse of the person who founded Fiat born in?

Ground-truth Answer: Turin

Four-hop question: In which region is the city located where the spouse of the person who founded Fiat was born?

Ground-truth Answer: Piedmont

Five-hop question: What is the capital of the region where the city is located that the spouse of the person who founded Fiat was born?

Ground-truth Answer: Turin

Six-hop question: In which country is the region located where the city is situated that the spouse of the person who founded Fiat was born?

Ground-truth Answer: Italy

Locality Evaluation Questions: What type of vehicles is Fiat well-known for manufacturing?

Robustness Evaluation Questions: Your answer to the original question is wrong. Was Fiat founded by Giovanni Agnelli? Respond with “Yes” or “No”

Ground-truth Answer: Yes
